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A METHODOLOGY TO PRODUCE GEOGRAPHICAL INFORMATION FOR LAND PLANNING USING VERY-HIGH RESOLUTION IMAGES

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Tese de Doutoramento em Geografia e Planeamento Territorial, Especialização em Detecção Remota e Sistemas de Informação Geográfica

Março de 2011

Tese apresentada para cumprimento dos requisitos necessários à obtenção do grau de Doutor em Geografia e Planeamento Territorial, Especialização em Detecção Remota e Sistemas de Informação Geográfica, realizada sob a orientação científica do Professor Doutor José António Tenedório e co-orientação da Doutora Ana Fonseca

Dissertação de Doutoramento em Geografia e Planeamento Territorial, Especialização em Detecção Remota e Sistemas de Informação Geográfica, elaborada no âmbito do projecto GEOSAT – Methodologies to extract large scale GEOgraphical information from very high resolution SATellite images (PTDC/GEO/64826/2006), financiado pela Fundação para a Ciência e Tecnologia, que decorreu no e-GEO – Centro de Estudos de Geografia e Planeamento Regional, da Faculdade de Ciências Sociais e Humanas, no quadro do Grupo de Investigação Modelação Geográfica, Cidades e Ordenamento do Território

Os trabalhos que culminaram na presente tese foram financiados pela Fundação para a Ciência e Tecnologia, através de uma bolsa individual de doutoramento (SFRH/BD/27671/2006).

FCT Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR

e GEO
Centro de Estudos de Geografia e Planeamento Regional
Faculdade de Ciências Sociais e Humanas . Universidade Nova de Lisboa

À minha família

ACKNOWLEDGMENTS

Dirijo o meu primeiro agradecimento aos meus pais, ao António e aos meus filhos pela estabilidade, encorajamento e equilíbrio emocional que me propuseram, sem os quais não teria sido possível desenvolver o trabalho aqui apresentado.

Gostaria ainda de agradecer a outras pessoas que me ajudaram no decorrer desta investigação.

Ao Prof. Doutor José António Tenedório, meu orientador científico, que me acompanhou em todas as fases do trabalho, e me disponibilizou todos os meios técnicos e total liberdade de investigação.

À Engenheira Ana Fonseca, minha co-orientadora, pela sua disponibilidade e apoio em todas as fases desta tese.

Ao Dr. Miguel Brito, pelo esclarecimento de todas as dúvidas em relação ao cálculo dos parâmetros solares e ao Nuno Gomes pela implementação do modelo SIG que permitiu avaliar o potencial solar de edifícios.

Aos meus colegas Bruno Neves, Carla Rebelo, Nuno Afonso, Sara Encarnação e Rossana Estanqueiro, que me ajudaram em diversas fases deste estudo.

Um agradecimento especial ao meu amigo Sérgio Freire, pelo apoio, motivação, disponibilidade, críticas, interrogações e direcções apontadas.

Aos meus colegas do projecto GEOSAT, pelo companheirismo, troca de ideias e pela partilha de todas as frustrações e alegrias ao longo destes 3 anos de trabalho conjunto.

À Fundação para a Ciência e Tecnologia, pelo apoio financeiro cedido sob a forma de uma bolsa individual de doutoramento.

À empresa Lógica, pela cedência dos dados LiDAR, que permitiram ir mais além na investigação proposta.

E a todas as pessoas que me apoiaram indirectamente durante o período em que decorreu este trabalho.

RESUMO

DESENVOLVIMENTO DE UMA METODOLOGIA PARA PRODUÇÃO DE INFORMAÇÃO GEOGRÁFICA PARA PLANEAMENTO TERRITORIAL, A PARTIR DE IMAGENS DE MUITO GRANDE RESOLUÇÃO ESPACIAL

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PALAVRAS-CHAVE: uso do solo, ocupação do solo, imagens, muito-alta resolução espacial, extracção de *features*, LiDAR, planeamento, monitorização do território

Actualmente, os municípios são obrigados a produzir, no âmbito da elaboração dos instrumentos de gestão territorial, cartografia homologada pela autoridade nacional. O Plano Director Municipal (PDM) tem um período de vigência de 10 anos. Porém, no que diz respeito à cartografia para estes planos, principalmente em municípios onde a pressão urbanística é elevada, esta periodicidade não é compatível com a dinâmica de alteração de uso do solo. Emerge assim, a necessidade de um processo de produção mais eficaz, que permita a obtenção de uma nova cartografia de base e temática mais frequentemente. Em Portugal recorre-se à fotografia aérea como informação de base para a produção de cartografia de grande escala. Por um lado, embora este suporte de informação resulte em mapas bastante rigorosos e detalhados, a sua produção têm custos muito elevados e consomem muito tempo.

As imagens de satélite de muito alta-resolução espacial podem constituir uma alternativa, mas sem substituir as fotografias aéreas na produção de cartografia temática, a grande escala.

O tema da tese trata assim da satisfação das necessidades municipais em informação geográfica actualizada. Para melhor conhecer o valor e utilidade desta informação, realizou-se um inquérito aos municípios Portugueses. Este passo foi essencial para avaliar a pertinência e a utilidade da introdução de imagens de satélite de muito alta-resolução espacial na cadeia de procedimentos de actualização de alguns temas, quer na cartografia de base quer na cartografia temática.

A abordagem proposta para solução do problema identificado baseia-se no uso de imagens de satélite e outros dados digitais em ambiente de Sistemas de Informação Geográfica.

A experimentação teve como objectivo a extracção automática de elementos de interesse municipal a partir de imagens de muito alta-resolução espacial (fotografias aéreas ortorectificadas, imagem QuickBird, e imagem IKONOS), bem como de dados altimétricos (dados LiDAR).

Avaliaram-se as potencialidades da informação geográfica extraídas das imagens para fins cartográficos e analíticos. Desenvolveram-se quatro casos de estudo que reflectem diferentes usos para os dados geográficos a nível municipal, e que traduzem aplicações com exigências diferentes. No primeiro caso de estudo, propõe-se uma metodologia para actualização periódica de cartografia a grande escala, que faz uso de fotografias aéreas

ortorectificadas na área da Alta de Lisboa. Esta é uma aplicação quantitativa onde as qualidades posicionais e geométricas dos elementos extraídos são mais exigentes. No segundo caso de estudo, criou-se um sistema de alarme para áreas potencialmente alteradas, com recurso a uma imagem QuickBird e dados LiDAR, no Bairro da Madre de Deus, com objectivo de auxiliar a actualização de cartografia de grande escala. No terceiro caso de estudo avaliou-se o potencial solar de topos de edifícios nas Avenidas Novas, com recurso a dados LiDAR. No quarto caso de estudo, propõe-se uma série de indicadores municipais de monitorização territorial, obtidos pelo processamento de uma imagem IKONOS que cobre toda a área do concelho de Lisboa. Esta é uma aplicação com fins analíticos onde a qualidade temática da extracção é mais relevante.

ABSTRACT

A METHODOLOGY TO PRODUCE GEOGRAPHICAL INFORMATION FOR LAND PLANNING USING VHR IMAGES

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KEYWORDS: land use, land cover, images, very-high spatial resolution, feature extraction, LiDAR, land planning, land monitoring

Currently, the Portuguese municipalities are required to produce homologated cartography, under the Territorial Management Instruments framework. The Municipal Master Plan (PDM) has to be revised every 10 years, as well as the topographic and thematic maps that describe the municipal territory. However, this period is inadequate for representing counties where urban pressure is high, and where the changes in the land use are very dynamic. Consequently, emerges the need for a more efficient mapping process, allowing obtaining recent geographic information more often. Several countries, including Portugal, continue to use aerial photography for large-scale mapping. Although this data enables highly accurate maps, its acquisition and visual interpretation are very costly and time consuming.

Very-High Resolution (VHR) satellite imagery can be an alternative data source, without replacing the aerial images, for producing large-scale thematic cartography.

The focus of the thesis is the demand for updated geographic information in the land planning process. To better understand the value and usefulness of this information, a survey of all Portuguese municipalities was carried out. This step was essential for assessing the relevance and usefulness of the introduction of VHR satellite imagery in the chain of procedures for updating land information.

The proposed methodology is based on the use of VHR satellite imagery, and other digital data, in a Geographic Information Systems (GIS) environment.

Different algorithms for feature extraction that take into account the variation in texture, color and shape of objects in the image, were tested. The trials aimed for automatic extraction of features of municipal interest, based on aerial and satellite high-resolution (orthophotos, QuickBird and IKONOS imagery) as well as elevation data (altimetric information and LiDAR data).

To evaluate the potential of geographic information extracted from VHR images, two areas of application were identified: mapping and analytical purposes. Four case studies that reflect different uses of geographic data at the municipal level, with different accuracy requirements, were considered. The first case study presents a methodology for periodic updating of large-scale maps based on orthophotos, in the area of Alta de Lisboa. This is a situation where the positional and geometric accuracy of the extracted information are more demanding, since technical mapping standards must be complied. In the second case study, an alarm system that indicates the location of potential changes in building areas, using a QuickBird image and LiDAR data, was developed for the area of Bairro da Madre de Deus. The goal of the system is to assist the updating of large-

scale mapping, providing a layer that can be used by the municipal technicians as the basis for manual editing. In the third case study, the analysis of the most suitable rooftops for installing solar systems, using LiDAR data, was performed in the area of Avenidas Novas. A set of urban environment indicators obtained from VHR imagery is presented. The concept is demonstrated for the entire city of Lisbon, through IKONOS imagery processing. In this analytical application, the positional quality issue of extraction is less relevant.

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LIST OF ABBREVIATIONS

ALOS	Advanced Land Observing Satellite
ALS	Airborne Laser Scanning
ALUM	Australian Land Use and Management Classification
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATKIS	German cartographic and topographic database (Amtliches Topographisch-Kartographisches Informationssystem
BAS	Buildings, Annexes and Shacks
CARTUS-AML	Land Use Map of Lisbon Metropolitan Area (*Carta de Uso do Solo da Área Metropolitana de Lisboa*)
CCD	Charge Coupled Device
CCDR	Commissions for Regional Development (*Comissão Coordenação para o Desenvolvimento Regional*)
CLC	CORINE Land Cover
CLUSTERS	Classification for Land Use Statistics: Eurostat Remote Sensing Program
CNIG	National Centre for Geographic Information (*Centro Nacional de Informação Geográfica*)
COS	Land Cover Map of Portugal (*Carta de Ocupação do Solo*)
CP	Control Point
DEM	Digital Elevation Model
DGOTDU	General Directorate of Territorial Management and Urban Development (*Direcção-Geral do Ordenamento do Território e Desenvolvimento Urbano*)
DGRF	Forest Institute (*Direcção Geral de Recursos Florestais*)
DL	Decree-Law
DMC	Digital Mapping Camera
DN	Digital Numbers
DR	Regulatory Decree
DSM	Digital Surface Model
DTM	Digital Terrain Model
EC	European Commission
EEA	European Environment Agency
e-GEO	Geography and Regional Planning Research Centre
EO	Earth Observation
ESA	European Space Agency
EU	European Union
EURMET	Urban Sprawl of Major Cities in South West Europe

FAO	Food and Agriculture Organization
GCP	Ground Control Point
GDS	Geographical Data Sets
GEOBIA	GEographic Object Base Image Analysis
GEOSAT	Methodologies to extract large scale GEOgraphical information from very high resolution SATellite images
GEOSS	Global Earth Observation System of Systems
GI	Geo-Information
GIS	Geographic Information System
GLCM	Gray-Level Co-occurrence Matrix
GMES	Global Monitoring for Environment and Security
GPS	Global Positioning System
HRV	High Resolution Visible
I&CLC2000	IMAGE and CORINE Land Cover 2000
IGeoE	Army Geographic Institute (*Instituto Geográfico do Exército*)
IGP	Portuguese Geographic Institute (*Instituto Geográfico Português*)
IGT	Territorial Management Instruments (*Instrumentos de Gestão Territorial*)
IHS	Intensity, Hue, Saturation
INS	Inertial Navigation System
IPCC	Portuguese National Geodetic, Mapping and Cadastre Agency (*Instituto Português de Cartografia e Cadastro*)
IRS-1C	Indian satellite
ISO	International Standards Organization
JRC	Joint Research Centre
LBPOTU	Urbanism and Planning Policy Framework Law (*Lei de Bases da Política de Ordenamento do Território e Urbanismo*)
LCM	Land Cover Map
LCMGB	Land Cover Map of Great Britain
LCMUK	United Kingdom Land Cover Map
LGN	Land Use Database of The Netherlands
LiDAR	Light Detection And Ranging
LULC	Land Use and Land Cover
MAD	Multivariate Alteration Detection
MAOT	Environment and Territorial Management Ministry (*Ministério do Ambiente e do Ordenamento do Território*)
MGAI	Geometric Model of the Image Acquisition
MODIS	Moderate Resolution Imaging Spectroradiometer
MOS	*Modes d'Occupation du Sol*
MS	MultiSpectral

MSS	Multispectral Scanning System
MURBANDY / MOLAND	Monitoring Urban Dynamics/ Monitoring Land Use Changes
NASA	National Aeronautics and Space Administration
NDG	Number of Different Grey-levels
nDSM	normalized DSM
NDVI	Normalized Difference Vegetation Index
NIIRS	National Imagery Interpretability Rating Scale
NIR	Near-Infrared
NLUD	National Land Use Database
NOAA	National Oceanic and Atmospheric Administration
NUTS	Nomenclature of Territorial Units for Statistics
OOTU	Monitoring Centre for Spatial Planning and Urbanism (*Observatório do Ordenamento do Território e Urbanismo*)
Pan	Panchromatic
PCA	Principal Component Analysis
PCS	Principal Component Substitution
PDM	Master Plan (*Plano Director Municipal*)
PIF	Pseudo-Invariant Features
PMOT	Municipal Plans (*Planos Municipais de Ordenamento do Território*)
PNPOT	National Program for Planning and Territorial Management (*Programa Nacional de Planeamento e Ordenamento do Território*)
PP	Design Plan (*Plano de Pormenor*)
ProCARTA	Produção de Cartografia Topográfica Oficial a Escalas Grandes
PROGIP	Support Program on Computer Management of Municipal Plans
PROSIG	Support Program for the Creation of Local Nodes of SNIG
PROT	Regional Plans (*Plano Regional de Ordenamento do Território*)
PU	Urban Plan (*Plano de Urbanização*)
PVGIS	Photovoltaic Geographical Information System
PWL	PieceWise Linear
RAN	National Agricultural Reserve (*Reserva Agrícola Nacional*)
REN	National Ecological Reserve (*Reserva Ecológica Nacional*)
REOT-M	Status Report of City Planning (*Relatório do Estado do Ordenamento do Território*)
RFC	Rational Function Coefficient
RFM	Rational Function Model
RGB	Red, Green, and Blue
RJIGT	Judicial Regime of the Territorial Management Instruments (*Regime Júridico dos Instrumentos Territoriais de Gestão*)
RMSE	Root Mean Square Error

SAR	Synthetic Aperture Radar
SMA	Spectral Mixture Analysis
SNIG	National Infrastructure for Geographical Information (*Sistema Nacional de Informação Geográfica*)
SNIT	National System of Territorial Information (*Serviço Nacional de Informação Territorial*)
SPIDER	Improving SPatial Information extraction for local and regional DEcision makers using very high resolution Remotely sensed data
SPOT	Satellite Pour l'Observation de la Terre
STRM	Shuttle Radar Topography Mission
TIN	Triangulated Irregular Network
TM	Thematic Mapper
TPL	Thin-PLate
UDR	Urban Dynamics Research
UK	United Kingdon
URL	Uniform Resource Locator
USA	United Sates of America
USGS	United States Geological Survey
VHR	Very-High Resolution
VIS	Vegetation, Impervious surface, and Soil

INTRODUCTION

Land Planning is a highly complex process aiming at a conceptual anticipation of future situations, through regulating and enforcing land use. Developing strategic orientations that induce future activities requires knowledge of the physical urban environment, and how it changes over time. These questions are inherently spatial in nature, but relevant geographic information is rarely available with the necessary detail (spatial, and temporal), making difficult the process of forming an opinion and subsequent decision-making.

Earth Observation (EO) is an independent data source, publicly available, which can help collect updated information at different levels of detail. However, images are *data* not *information,* meaning that an image processing methodology must be selected and applied in order to transform image data into information pertinent for land planners. In similar contexts, such methodology should be replicable, leading to consistent and comparable products.

Remote sensing images, besides their mapping capabilities, can also be used in analytical situations. Urban planners need information on phenomena like the city's spatial arrangement, the available green area per capita, where traffic congestions can be improved, the dynamic evolution of the building construction activity, the implementation of regional/local strategies, the identification of spatial and temporal patterns of urban sprawl over long or short time periods, among many others. Remote sensing has the distinctive capability of providing a comprehensive set of tools for characterizing the Earth's surface, enabling production of specific-products for decision-makers.

In Portugal, current land use maps are still produced based on visual interpretation and field survey. Such mapping task is labor-intensive, and the resulting classification is subjective and its replicability is difficult if not performed by the same technitian. Consequently, conclusions about land use changes between consecutive map updates can be biased. Nevertheless, maps such as the CORINE Land Cover, are generally good products that enable comparisons between European countries. Furthermore, subjectivity can be diminiuished if well trainned photo-interpreters are selected. In a semi-automatic land use mapping approach, the subjectivity inherent to the manual identification and delimitation of the classes is reduced and the possibility of repeating the classification process in subsequent time-periods is much favored. Nevertheless, land use mapping is an expensive process, and its cost is also dependent on the effort to classify with more or less detail the objects of interest. From a land planning perspective, it is worthwhile to investigate different levels of information abstraction regarding scale, class detail or minimum mapping unit, that allow characterizing the most common situations land planners have to deal with. Based on that identification, it is possible to orient the land use mapping towards different applications that require specific products. The identification of the processes and the characteristics that must be monitored will directly influence the effort and the time spent for land mapping and, consequently, the mapping cost.

The thesis was developed under the framework of the project GeoSAT – Methodologies to extract large scale GEOgraphical information from very high resolution SATellite images, funded by the Foundation for Science and Technology. The research project, that took place between 2008 and 2010, involved the Lisbon City Hall, and aimed at developing methods to expedite the production of geographic information for municipal planning and land monitoring. The project and the thesis work were hosted by e-GEO – Geography and Regional Planning Research Centre, from the New University of Lisbon. The centre has a long tradition in both theoretical and policy-oriented research on urban and regional development, being remote sensing one of the fields of interest and competence.

In the thesis context, some of the concepts used do not have yet a standard definition, requiring an initial clarification. The main data source about the Earths' surface used in this work is Very-High Resolution (VHR) images. The term VHR is used for images with spatial resolution equal or greater than 1 m. Furthermore, two terms are used as synonyms – feature and object. An image object is a group of pixels in a map. The pixels are grouped into meaningful objects based on homogeneity criteria according to their attributes, such as shape, color and relative position to other objects.

English was the chosen language for this thesis, along with the conventions for representing numbers.

OVERALL RESEARCH OBJECTIVES

Land use information is a key factor in the spatial planning system. Knowledge regarding its extension, pattern, and modification over time, is the core of physical planning. Remote sensing data is the elected source of information about the Earth's surface, and the semi-automatic methodologies most suitable for extracting that information are the subjects of this thesis.

The thesis deals with the links between the following domains: land planning, geographic information science, remote sensing, land use, and land use mapping. The main objective is to develop methods for automatic extraction of geo-spatial information from aerial or satellite images, to be used for municipal planning. Evaluation of different land products, having distinct levels of detail, is performed, and presented as case studies.

A distinction between cartographic and analytical applications is made. For cartographic purposes, the geographic element that the municipalities most require information about is Buildings. The present framework, used to map buildings at the municipal level, is analyzed, and an alternative based on remote sensing data is proposed. In this situation, careful attention is paid to the correct identification and delimitation of the elements of interest (i.e., buildings), using positional, geometric and thematic accuracy indices. Regarding analytical applications, different situations that demand land use information, with different levels of detail, are presented. The attention in these cases is not on the compliance with map specifications, but rather to derive quantitative information, with known quality, based on VHR data that can be used in different decision-making tasks.

Based on the above discussion, the research objectives can be summarized as follows:

- To contribute to solving the needs for updated land information;
- To evaluate the main problems concerning VHR imagery classification for the stated purposes. In one hand, there are different approaches for image classification. An overview focusing on the advantages and disadvantages of the most relevant methods described in the literature is presented. On the other hand, are the images' characteristics, like spatial and spectral resolution, that can limit the quality of the information extracted;

- To investigate which Territorial Management Instruments and which planning processes intended for the municipal scale, require geographic data, and how remote sensing can be used to provide such information;
- To assess the needs of Portuguese municipalities regarding geographic information. A characterization of how the geo-data is valued and used in a municipal department allows inferring knowledge about what are the main concerns regarding these data. Furthermore, knowing what are the most used geographic elements and respective scales, as well as the required update period, can help in designing remote sensing-based products;
- To provide a semi-automatic methodology for extracting geographic information, that allows a good balance between performance (quality vs. time), cost, and user-friendliness, since these constitute important criteria for adoption by a municipality department;
- To analyze the constraints between map-scale issues and the detail of the information extracted for a certain application;
- To propose a new approach for explicitly incorporating quantitative mapping standards in the quality assessment of large-scale elements extracted from VHR satellite imagery;
- To identify and delimit urban changes using VHR geographic data, thus providing the basis for fast and effective visualization, a key element of building a land monitoring system based on EO data.

RELEVANCE AND CONTRIBUTIONS

Presently, the cartographic framework for municipal land planning is based on the compliance with very demanding and complex technical specifications. To obtain such large-scale topographic maps with the required quality, a great effort in terms of human and financial resources must be supported by the municipalities. Therefore, the spatial information regarding land use is only produced when the Master Plan is prepared. In the Portuguese land planning system, the plans' revision takes place every 10 years, the legal term for local plans, but longer periods are common. Such update periodicity does not reflect the dynamic nature of the land use, hampering the daily work of the departments that deal with geographic information on a daily basis. In fact, many situations that occur in the municipal context such as updating cadastral databases, management of urban areas, street maintenance and construction, or planning activities for possible disasters like earthquake or flooding, all require expedite production of digital maps at large-scale.

Using remote sensing data to produce maps, based on semi-automatic methods, that comply with the thematic detail and the positional quality of the large scales used in the municipal planning (e.g., 1:10 000 and higher), is still a challenge. In this thesis, classification of remote sensing data is not proposed as an alternative process for replacing the present cartographic framework, which produces very detailed information, for many themes, and with very high quality. In fact there are still limitations concerning the effectiveness of full automatic methods, especially the ones aimed to be applied over a complex landscape containing many different classes of objects, also with different spectral characteristics. These methods should not be expected to deliver final products, but to facilitate image analysis and interpretation, in a more or less interactive workflow.

The contribution of the work presented here is rather the coexistence of two levels of information in the municipal Geographic Information System (GIS): a 1st level of official topographic cartography produced at least every 10 years with conventional and more accurate methods, and a 2nd level with less detailed thematic and geographic information but with a higher temporal resolution, with known accuracy specifications, from processing of mono VHR satellite images. Such level of information can be used for indicating places were potential changes have occurred and must be investigated by a technician that will decide upon its veracity, or to allow extracting quantitative/qualitative information about the evolution of land use patterns over time, or to supply other relevant data with geographic representation.

THESIS ORGANIZATION AND OUTLINE

The thesis is divided into seven chapters. The scientific background of the selected methodology is described in the first four chapters. Chapter 1 presents the conceptual foundations of urban landscape analysis based on remote sensing data, and characterizes the Land Use Land Cover (LULC) maps available in Portugal. Chapter 2 describes the methodological steps involved in land cover mapping with remote sensing data. Chapter 3 exposes the algorithms commonly used in the mapping process to retrieve land information from image data, and Chapter 4 is a literature review that presents the theoretical framework that supports the design and implementation of the applications that will be developed later as case studies.

Chapters 5 and 6 are the core part of this dissertation. Chapter 5 presents the land planning system in Portugal, and characterizes the geographic information necessary to implement it. Furthermore, the need for updated geographic information at the municipal level is assessed through a survey and the results are discussed. Chapter 6 presents four case studies to demonstrate the usefulness of geographic information extracted form VHR imagery, for cartographic and analytical applications, at the municipal level.

Finally, conclusions and future research are outlined in Chapter 7.

1. CONCEPTUAL FOUNDATIONS OF URBAN LANDSCAPE ANALYSIS BASED ON REMOTE SENSING DATA

The purpose of the present thesis is to study LULC mapping in urban areas, using VHR imagery data. Through LULC mapping, we can measure the extent and distribution of thematic classes, examine the interaction between those classes, identify suitable places for certain activities, detect changes, and plan for the future. Furthermore, LULC maps serve as basic data sets for the production of more complex information on other topics such as municipal plans for land management, or studies on environment impacts of new infrastructures like railroads or highways.

LULC mapping is generally done by processing imagery obtained from remote sensing instruments, like aerial photographs or satellite images. Traditionally, the cartographic framework is based on the visual analysis of aerial photographs, (Herold et al., 2003a). Alternatively, semi-automatic algorithms for digital image classification, together with visual analysis, can also be used for LULC mapping. The choice of aerial photographs for large scale mapping production is directly related to their high spatial resolution. Moreover, the satellite images have only recently begun to emerge as an alternative data source, due to technologic advances that allow capturing images with higher spatial resolutions.

However, despite the emergence of new sensors with improved spatial characteristics and the rapid development of new digital image processing techniques, there is a time lag between the presentation of research results among the scientific community and its implementation by government agencies (Netzband et al., 2007). Furthermore, although high spatial resolution generally allows improved discrimination of urban elements, the effects of relief displacement, shadows from tall structures and other distortions can complicate the information extraction from VHR images of urban areas with tall buildings or significant relief.

The following issues should then be taken into account when evaluating the usefulness of EO images for urban mapping (Donnay et al., 2001):

- Are objects relevant to urban planning, intrinsically discernible in the remote sensing images with respect to characteristics such as spatial, spectral, and temporal resolution?

- What are the characteristic properties of urban objects that allow identifying and classifying them in the image data set?
- Are the current methodologies for collecting thematic information from EO images appropriate to extract this kind of objects?

This chapter debates the concepts and techniques that characterize the detection and interpretation of urban elements in VHR remote sensing data. The following sections characterize the object of study - urban object - in its multiple facets. On one side, the spatial, temporal and spectral characteristics of the urban objects are formalized as well as its dynamics. On the other hand, it is described how the geographic information can be structured and analyzed in a GIS. Finally, an historical review of the contribution of remote sensing data in the study of urban elements is presented and the question of the adequacy and relevancy of the imagery analysis to study the urban scale is discussed. The last section presents the LULC maps available in Portugal, and analyses the national mapping projects, considering the data source for land information, the nomenclature, the methodologies used for mapping, and the technical specifications.

1.1 URBAN ENVIRONMENT

Although intuitively the identification of an urban area is a relatively easy task, its formalization is not. Indeed, there is no universal method for identification of urban areas (Toit and Cilliers, 2010). This concept tends to vary from country to country and is generally defined based on historical, political, cultural and demographic characteristics. For example, Peru defines an urban area based on the density of buildings (structures by area) while Japan identifies a region as urban based on the total number of inhabitants, and the United States uses the population density (Weeks et al., 2003). In Portugal, the population density is also adopted as the parameter that differentiates urban areas from rural ones.

The signature of a constructed urban environment is represented, of course, by built structures (buildings, roads, sidewalks) but also by various types of vegetation (parks, gardens, agricultural areas), bare soil and water bodies (Barnsley and Barr, 2000). In contrast to the natural environment, the urban structures are built with distinct landscape objects having well defined boundaries (Couclelis, 1996).

The urban environment is a physical representation of human activities and as such is likely to be measured. There are a number of data sources that can be used to describe the variability, allowing the quantification of the urban environment. Examples are the census data (which identifies buildings and their uses), cadastral maps (that show properties subject to different taxes), or even maps of urban infrastructure such as water, sewer lines or high voltage power lines.

Alternative data sources are the images collected by remote sensing systems that allow inferring the urban element through the analysis of the spectral and spatial characteristics recorded. However, the images are "virtual" representations of the city, because the pixels quantify the surface status of the bodies through the coding of the intensity of the electromagnetic signal, and do not qualify the elements that compose the city. The intensity of the signal is encoded into digital levels which correspond to urban physical elements (buildings, streets, vegetation, water, etc.) having very different functions.

High-spatial resolution images offer two types of spatial elements: continuous elements (such as the classes of LULC), and discrete objects (such as buildings) that are distinguishable from the background surface (Weeks et al., 2005). The continuous elements represent the composition of the area under analysis, while the discrete objects represent the area configuration. Greater attention has been given to the composition than to the configuration (Bian and Xie 2004), which has resulted in improved ability to quantify the former and lower ability to quantify the latter. The composition refers to the proportional abundance of a particular kind of land class in a given region, without considering its spatial arrangement, position or location in the landscape mosaic. The composition is extracted from the images through digital techniques. There are several landscape metrics, which aim to describe the composition: proportional abundance of each class, richness, dominance and diversity. However, configuration is much more difficult to obtain and quantify than composition (McGarigal et al., 2002). The configuration relates to the space, arrangement, position or orientation of patches within the class or landscape. A number of configuration metrics can be formulated either in terms of the individual patches or in terms of the whole class or landscape. Representative metrics that describe the configuration include patch size, distribution and density, patch shape complexity, core area, isolation/proximity, contrast, dispersion, contagion and interspersion, subdivision and connectivity (McGarigal et al., 2002).

The next sections describe how remote sensing can be used to observe, estimate quantify and monitor changes over urban areas.

1.1.1 TEMPORAL CONSIDERATIONS

When studying urban phenomena, it is necessary to assess what time, or time period, is more appropriate for analysis. This depends on the dynamics to be identified. Jensen and Cowen (1999) identified three types of temporal resolution when analyzing urban environments:

- The first type relates to the dynamic characteristics of the processes of change in urban areas. If the goal is to monitor works on public roads, then the period of analysis may be a few months. However, if you want to monitor a process of urbanization, then the period of analysis may be a few years;
- The second type of temporal resolution is the revisit range of urban space for data collection. This feature varies depending on the data source. If the selected source is satellite images, the temporal resolution varies from satellite to satellite, going from daily capture (QuickBird) to within three days (IKONOS-2) or longer periods. If the source is aerial photography, planning the aerial flight has an associated cost that must be taken into account. Furthermore, the need for field survey, also influence the frequency of data collection;
- The third type of temporal resolution is related with the needs of planners and land managers. For the local level, it may be necessary to have updated information, e.g., on an annual basis, while on regional or national levels that requirement can be reduced to 5 years or a decade (e.g., definition of regional plans, updating cadastral information).

1.1.2 SPECTRAL CONSIDERATIONS

When extracting urban information from remote sensing data by visual interpretation, high spatial resolution (< 5 m) is often more important than high spectral resolution (i.e., with large numbers of bands) (Jensen and Cowen, 1999). For example, the detection of individual buildings requires a spatial resolution from 0.25 to 5 m, while one band from the visible region of the spectrum (blue, green or red) with that resolution, is sufficient. However, there must be sufficient spectral contrast between the object of interest and what surrounds it, to allow its classification.

On the other hand, if the extraction method is imagery classification, than the spectral dimension is also very significant (Herold et al., 2003b). In fact, while high spectral resolution is not a rigid request for urban mapping; there are however, portions of the electromagnetic spectrum especially useful to extract certain types of urban cover. The identification of buildings is best achieved in real color or panchromatic images, while the identification of urban areas with green cover (e.g., leisure parks or single-family residences) is best accomplished by examining the visible and infrared regions of the spectrum.

To isolate the spectral signature of an urban object is relatively straightforward. But to consider only the spectral signature for feature extraction is much more difficult. There are several reasons for this fact. First, urban elements of the same LULC class (e.g., roofs), but having different angles, may have different levels of spectral reflectance (Figure 1). A roof of slate with zero degrees of tilt has a reflectance three times greater than the same roof of slate with a thirty degree tilt. The diffuse reflectance is therefore strongly influenced by the surface roughness of urban objects.

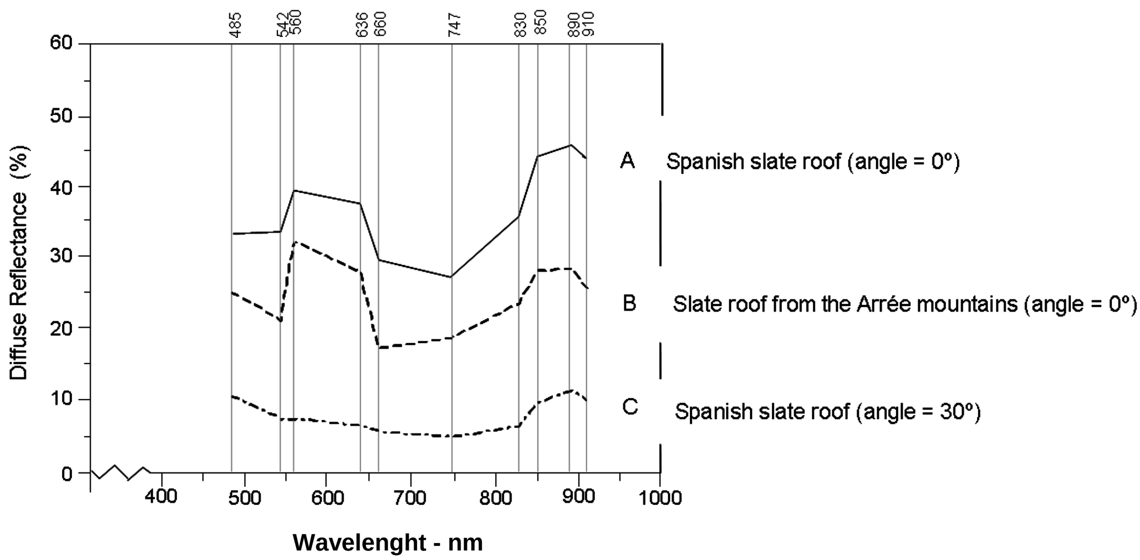


Figure 1. Measures of reflectance of roofs typical of Spain and Southwest of France

Secondly, because the mineral surfaces of different LULC classes have relatively similar spectral reflectance (e.g., parking lot is spectrally similar to grey-brown tile roof) (Figure 2, Figure 3).

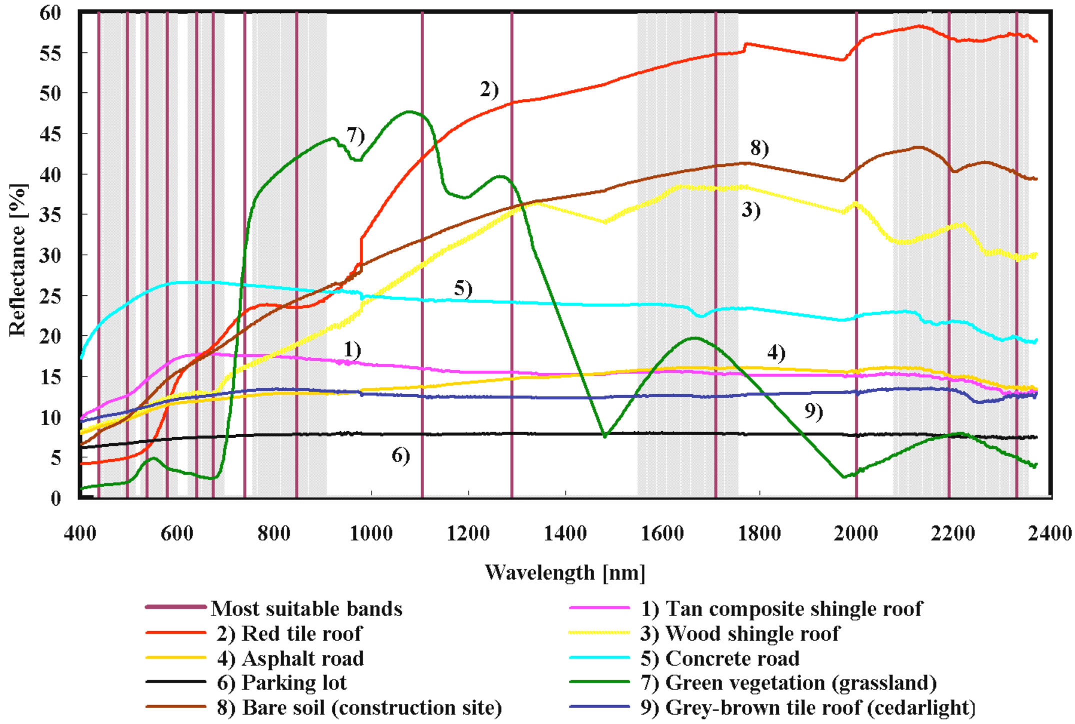


Figure 2. Example spectra of typical urban land cover from the Santa Barbara urban spectral library (source: Herold et al., 2003b)

Figure 3. Example of a typical urban landscape in Lisbon city

Furthermore, the effect of shadow is a problem at all resolutions, and spectra containing shadowed land cover should be analyzed with special attention. In terms of road type mapping this effect can result in severe misclassifications when shaded roads are mapped as “dark vegetation” (Herold et al., 2003b) (Figure 4, Figure 5).

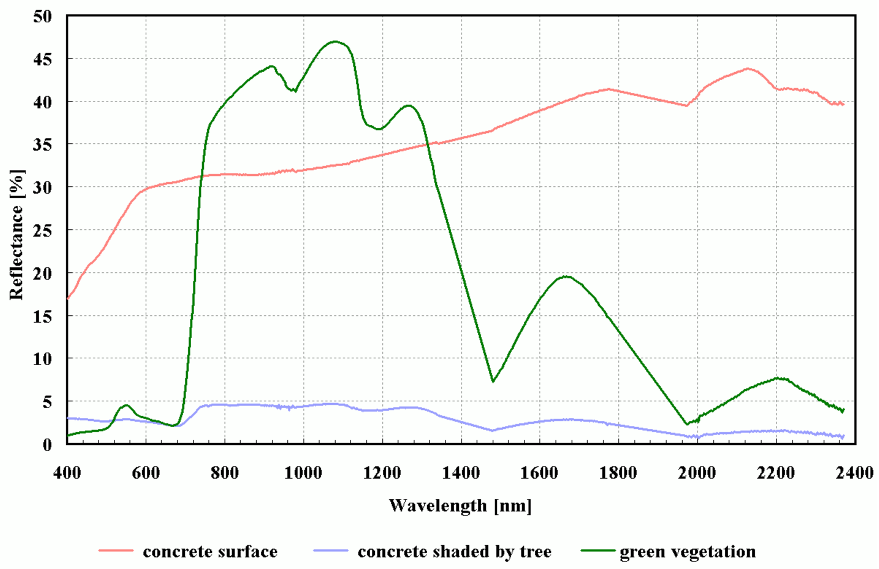


Figure 4. Spectra of concrete surface, green vegetation and concrete surface shaded by tree from the Santa Barbara ASD urban spectral library (source: Herold et al., 2003b)

Figure 5. Shadowing effect in a dense urban area, located in Lisbon city

One can conclude that, in the urban environment, the spectral discrimination of isolated features is not enough. On one hand, other types of data such as Light Detection and Ranging (LiDAR) must be included to separate highly-reflective impervious surfaces such as bare soil (harvested urban agriculture areas, for example) from tall buildings that have similar levels of reflectance. One the other hand, urban remote sensing must ally the spectral recognition of features with the spatial recognition (spatial organization of spectral signatures) (Bähr, 2001).

1.1.3 SPATIAL CONSIDERATIONS

A photo-interpreter uses features such as tone, color, texture, shape, size, orientation, pattern, shadow, location and context of objects in urban areas to identify and assign a class (Jensen, 2005). The elements of geometric interpretation of image (shape, size, orientation, pattern and shadow) are particularly useful in VHR data. A general rule concerning the spatial resolution, based on the Shannon's theory of information, is the need for a minimum of four spatial observations (i.e., pixels) within an urban object to identify it. In other words, the spatial resolution of a sensor should be half the diameter of the smallest object of interest. For example, the identification of a terrace with a 5 m size requires an image with resolution greater than or equal to 2.5 m (Jensen and Cowen, 1999).

Welch (1982) identified the spatial resolution of remote sensing data as the most important factor for the study of urban areas, and suggested resolutions in the order of 5 to 10 m as being indicated to characterize urban environments. While in the 1980s/1990s this limitation existed in fact for satellite images, with the new generation of space-based sensors capturing images at resolutions up to 0.41 m (GeoEye-1), this restriction no longer subsists. However, how can one know what spatial resolution to use for a specific application? One way to assess the level of interpretation of an image is to use the Civil National Imagery Interpretability Rating Scale (NIIRS) developed and maintained by the American Committee on Imagery Resolution Assessments and Reporting Standards. NIIRS characterizes the usefulness of images for intelligence purposes. NIIRS uses a 10 level scale, with several interpretation tasks or criteria at each level. These criteria indicate the amount of information that can then be extracted from an image, at a given interpretation level (Irvine, 2003).

Fonseca (2004) evaluated the information content of an IKONOS image (multispectral bands, panchromatic, and pansharp) using the Civil NIIRS. The image used in the study covered a large area of the municipality of Lisbon. The author found that the IKONOS imagery fulfilled all the tasks of the first three levels of NIIRS and some tasks of the 4th level. The first three levels include, for example, the detection of highways with multiple lanes (level 1), the detection of aircrafts in an international airport (level 2) or detection of vehicles (level 3). Level 4 is more demanding, and includes tasks such as detecting fallen trees that block roads or individual concrete barriers/obstacles. Some tasks can only be met with pansharp images (i.e., multispectral bands merged with the panchromatic image) due to enhanced spatial resolution. For comparison, a *Satellite Pour l'Observation de la Terre* (SPOT) image of the same area, with the same characteristics (multispectral, panchromatic and pansharp bands) but with 20 m of spatial resolution, was also analyzed, having completed only the first and second levels of NIIRS.

The company Emap International (Nale, 2002) also made an assessment of QuickBird imagery (panchromatic and multispectral bands) and characterized its interpretation into NIIRS levels 5/6. Those levels indicate that, for example, electric or telephone poles (level 5), or individuals when not in group (level 6), can be identified.

Originating in landscape ecology, spatial metrics can be employed to measure the heterogeneity of landscapes at different spatial scales based on categorical patches or elements. These are defined as quantitative indices that describe the structure and pattern of a landscape, and were developed based on the Shannon's theory of information and the fractal geometry. The landscape description is based on the concept of patch. A patch is then defined as the basic element in a landscape. A landscape does not contain a single patch mosaic but rather a hierarchy of patch mosaics across a range of scales. Therefore, patch boundaries are only meaningful when referenced to a particular scale. A spatial metric can then quantify the spatial heterogeneity of individual patches, all patches of the same class or the entire landscape as a collection of patches (Herold et al., 2003a).

There is currently a variety of landscape indices proposed. Table 1 presents some metrics used in urban studies. A more detailed description of the mathematical formulas can be found in McGarigal et al. (2002). Many metrics are intuitive values such as the percentage of landscape covered by class, the patch density, the patch's size and standard deviation. Some metrics, like Contagion, measure the extent to which landscapes are aggregated: landscapes with large contiguous patches are described by high rates of contagion, whereas landscapes dominated by a relatively large number of small or fragmented patches, have a low contagion rate. The fractal dimension, on the other side, describes the complexity and fragmentation of a patch based on a perimeter-area ratio. The more complex and fragmented are the patches, the higher is its perimeter and its fractal dimension. Cohesion measures the physical connectivity of the land cover classes and increases with the aggregation of the patches that constitute a class.

Herold et al. (2003a) conducted a study where 22 metrics were tested in order to characterize the urban environment with IKONOS images covering 170 km of the coast of Santa Barbara, California, United States of America (USA). The authors concluded that building configuration was best characterized by area coverage, the regularity of the spatial arrangement (Nearest Neighbor metrics), the dominance of one large building structure (largest patch index), and the spatial heterogeneity of the individual building objects (edge density). Contagion, as a measure of the overall spatial heterogeneity of a land-use region, provided another important land-use discriminator.

Table 1. Examples of landscape metrics used in urban studies

Metric	**Description**
Percentage of Landscape	Sum of area of a given class (m^2) divided by the total area and multiplied by 100 (to convert to a percentage)
Patch density	Number of patches of a given class divided by total landscape area
Mean patch size	Average size of patches of a given class
Edge density	Sum of length (m) of all edge segments in the landscape, divided by the total area of the landscape (m^2) and multiplied by 10,000 (to convert to hectares)
Largest patch index	Area (m^2) of the largest patch of a given class, divided by the total landscape area (m^2) and multiplied by 100 (to convert to a percentage)
Nearest Neighbor distance	Distance (m) to the Nearest Neighbor patch of the same type, based on shortest edge-to-edge distance
Fractal dimension	Twice the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2)
Shape index	Patch perimeter (m) divided by the square root of patch area (m^2), adjusted by a constant to adjust for a circular standard (vector) or square standard (raster).
Cohesion	Standard Perimeter-area ratio
Contagion	Equals 1 plus the sum of the proportional abundance of each patch type multiplied by number of adjacencies between cells of that patch type and all other patch types, multiplied by the logarithm of the same quantity, summed over each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage). Measures the probability that a cell of a patch is adjacent to another cell of a patch from the same class
Patch richness	Number of different patch types present within the landscape boundary

1.1.4 URBAN CHANGE DYNAMICS

Information derived from remote sensing can potentially give a synoptic, consistent and instantaneous view of the surface at one, or more scales. Through the combination of such views, changes in the urban status can be detected, making urban remote sensing a valuable contribution to research in urban geography and planning. Mapping land use change provides a historical perspective and an assessment of the spatial patterns, rates, correlation, trends, and impacts of that change.

When characterizing urban dynamics, two key elements must be considered: the available space in which the process of growth occurs, and the period during which this development takes place (Batty et al., 1999). There are thus two ways to address the urban dynamics: the temporal and spatial dynamics.

The **temporal dynamics** can be characterized as fast, medium or slow, depending on the time frame of occurrence of the territory's transformation. Temporal urban databases have immediate applications in monitoring urban sprawl, watershed analysis, environmental assessment, hydrologic modeling, land surface degradation, and developing predictive modeling techniques to better forecast future areas of urban growth.

The **spatial dynamics** can occur in two ways. On one hand, there may be the occupation of new territories, e.g., formerly rural areas are converted to new urban uses. On the other hand, there may be a more intensive occupation of a site, while maintaining the same land use, e.g., changing from a residential area of low-density to a higher-density one. Any of these changes leads to a dynamic history of urban expansion or intensification, respectively.

1.2 CONTRIBUTION OF REMOTE SENSING DATA TO STUDY THE URBAN CONTEXT

Remote sensing imagery has been used for decades to study the Earth's surface. Regarding the urban environment, aerial imagery has been the most common data source for mapping human activities (Vu et al., 2009). Only recently, satellite images have gained interest, as alternative data sources for mapping urban areas. The following sections address the usage of remote sensing data for studying the urban environment.

1.2.1 AERIAL AND SPACEBORNE IMAGES

Remote sensing is the observation of the elements in the surface (land and ocean) and atmosphere, from a distance, using sensors onboard airborne or spaceborne platforms. The difference between the images captured from these two platforms is in their physical collection. In fact, today one can choose to use images collected by frame-based aerial cameras, Charge Coupled Device (CCD) digital cameras, thermal cameras, LiDAR, laser scanner, pushbroom scanners or by Synthetic Aperture Radar (SAR). In this section we will focus our attention in analogue and digital cameras.

Aerial photographs are obtained by airborne sensors. Of fundamental importance to the quality of aerial photographs is the camera used to obtain the images. Two broad types of airborne cameras are used: film-based and digital cameras. In analogue film-cameras, the collection of information occurs through a chemical reaction that occurs in the photographic emulsion. With photography, there is the possibility to vary the type of lens. The goal is to choose different focal distances depending on the mission. Thus it is possible to vary the acquisition scale while maintaining the flight height or vary the height of the flight maintaining the scale. The films used in land cover mapping campaigns are generally sensitive to the visible and near infrared regions of the electromagnetic spectrum. Alternatively, digital cameras can also be used: the image acquisition is done by charge-coupled devices (CCD sensors), and the spectral and spatial resolutions are characteristics of the camera (sensor) and not the film. In digital images, the recorded reflectance is stored digitally instead of on film. But typically, panchromatic or color digital pictures are obtained.

The first aerial photographs appeared in 1858 and have been used since then to study urban areas. Green (1956) developed a method to analyze the social structure in 17 urban residential areas in Alabama, USA, based on variables taken from black and white aerial photographs. The indices were created based upon characteristics: number of dwelling-units per structure, combinations of structure types, and location in terms of major land use characteristics. Noin (1970) estimated the rural population of Morocco by analyzing aerial photography. The number of houses in rural areas was determined and a measure of household of each house was applied to estimate the population. Henderson and Utano (1975) studied the potential of aerial photographs to assess the socioeconomic conditions of housing. Applying a regression analysis, in Albany, USA, they determined the importance of urban density in the housing quality in single households. The authors concluded that there was a linear relationship between density and the average value of homes, the average value of hire contracts, the average family income and the average number of rooms per unit. Lo (1979) studied the usefulness of aerial photographs of historic dates to assess the patterns of distribution of illegal neighborhoods and quantify changes in Kai Tak, Hong Kong. Lo (1989) estimated the population in Rhode Island, USA, using census data to extract the houses from aerial photos.

However, in most applications with aerial photography, information is obtained through visual analysis done by specialized technicians. This technique requires much training and experience and is not necessarily replicable from place to place and from time to time. Also, human interpretations are subjective, and are vulnerable to inconsistency and error. As a result, there is a need for new approaches to reduce or eliminate these difficulties associated with traditional aerial photograph analysis (Morgan et al., 2010).

Alternatively to the traditional film-based aerial photography, there are images obtained with sensors developed for remote detection that capture, through a digital process, the energy reflected by the different elements on the surface of the Earth. There are also sensors sensitive to thermal radiation, but most commercial sensors are confined to the region of the visible and near infrared. The light reflected by the elements on the surface, and captured by the sensor, is then converted into a Digital Number (DN) that constitutes the image. Through the analysis of the DNs is then possible to extract information about the elements on the surface and study their dynamics. Donnay et al. (2001) refer three generations of spaceborne remote sensing sensors. The first generation of instruments operated between the 1970s to early 1980s, and is represented by the Landsat's satellite Multispectral Scanning System (MSS). The Landsat MSS has a spatial resolution of 79 m, which limited its use for detailed urban mapping. The second generation of sensors launched in the 1980s, included the Landsat Thematic Mapper (TM) with spatial resolution of 30 m and the SPOT High Resolution Visible (HRV) with 20-m spatial resolution Multispectral sensor and a 10-m resolution panchromatic sensor. Although this second generation provided spatial resolutions finer than the previous one, it was not significantly better for classification of urban areas (Aplin, 2003) and results could even be poorer because although the spatial resolutions continue to be inferior to the spatial resolution of the urban elements, there were then more pixels wrongly classified (Toll, 1985, Martin et al., 1988). These events led to the development of sensors more accurate than those of the second generation. This third generation of sensors took advantage of the end of the Cold War that favored the de-classification of military technology (e.g., images from the 1960s to 1980s, captured by the Corona spy satellite were released). Also, from a space borne perspective, this became possible in 1994, when the United States government made a decision to allow commercial companies to market high-spatial resolution satellite remote sensing data for civil applications (Glackin, 1998). In particular, the IKONOS-2 satellite (Space Imaging Inc.), launched in 1999 with 4 m resolution in multispectral mode and 1 m in panchromatic mode, and the QuickBird-2 satellite (DigitalGlobe Inc.), launched in 2001 with 2.44 m resolution in the multispectral mode and 0.61 m in the panchromatic mode, allowed the scientific community to explore more detailed mapping procedures. These new sensors for EO now meet the recommendations of Welch (1982) concerning required resolutions of the order of 5 m, or less, for urban studies.

1.2.2 TECHNICAL CONSIDERATIONS

The classification of digital images is a major landmark on remote sensing since the process that can be implemented on computer and be automatically repeated, using other images, different locations or dates. The algorithms for classification have evolved with the characteristics of images captured by satellites, especially with the spatial and spectral resolution. The first commercial satellite to be launched was the Landsat 1 in 1972. Given the low spatial resolution of 80 m of this sensor, its use in urban studies was very limited. Later, with the availability of Landsat-TM and SPOT-HRV, with 30 and 20 m resolution respectively, multispectral information with a resolution compatible with urban studies became available, but only for regional scales (e.g., less than 1:50 000). The limitation imposed by these sensors' low spatial resolution has been overcome with the launch of a new generation of sensors, with resolutions greater than 10 m (Treitz and Rogan, 2004). The release of images of high spatial resolution as those obtained by the IKONOS or QuickBird satellites, led to the growth of digital classification studies in urban areas. Indeed, satellite images have now resolutions compatible with the criteria of large scale mapping, and allow the characterization of natural and anthropogenic surfaces (Figure 6). The more heterogeneous the units of LULC are and the more fragmented the landscape is, the higher is the spatial resolution required (Chen et al., 2004). Thus, the use of VHR images is extremely important in the urban context as its spatial scale allows a more detailed mapping of individual elements when compared with that obtained with medium-resolution images (Thomas et al. 2003).

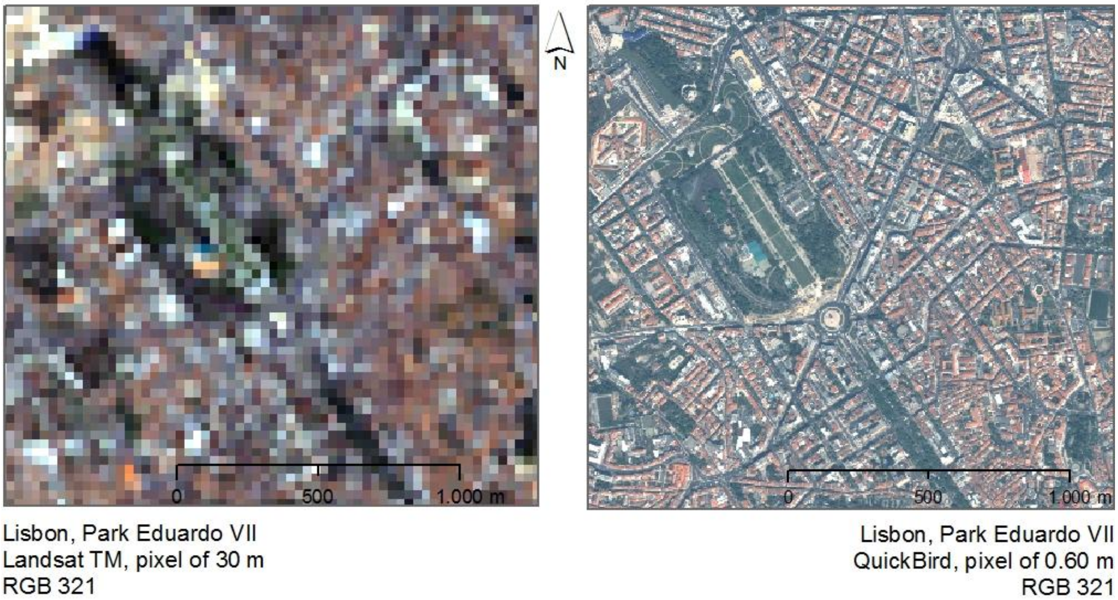


Figure 6. Information content variation due to different spatial resolutions

Paradoxically, this increase in spatial resolution did not produce maps with higher levels of quality (Barnsley and Barr, 2000). Indeed, initial studies performed on images with medium-resolution, with traditional multispectral classifiers (i.e., at the pixel level), in urban areas, produced maps with low accuracy (Forster, 1985; Toll, 1985; Martin et al., 1988). The explanation for this fact lies in the "noise" introduced by the increase in resolution, i.e., many areas that would be uniform in images of previous sensors become spectrally heterogeneous in higher spatial resolution images. The low performance of the images in the urban studies contributed to the "mistrust" and the skepticism with which the majority of planners look at this data source (Donnay et al., 2001).

But far from being a "noise" unwanted, the existing pixel to pixel variability is indeed a signal and a potential source of information on the properties of the urban environment. The initial "problem" arises from the inadequacy of traditional methods of digital image processing (e.g., multispectral classification algorithms at the pixel level) to extract useful information from data, rather than a limitation of the data itself (Barnsley and Barr, 1996). Let us take the example of a neighborhood of single-family houses (houses with gardens). If the goal is to classify it as a residential area, then applying an algorithm that operates at the pixel level will not produce the desired result.

In fact, in that type of classification, those pixels corresponding to the houses will be classified as urban areas and those pixels corresponding to the gardens will be classified as vegetation. This example shows how complex is the extraction of thematic information in urban areas, given the mixture of artificial and natural elements. Then, a higher level of structural information plays a key role in the LULC classification. To facilitate the understanding and identification of spatial patterns and/or spatial arrangement of artificial elements, additional spatial indicators have to be extracted from images.

While visual analysis continues to be widely used, there was a large investment in developing methods for automatic classification of VHR images. In fact, VHR imagery, like aerial images, have been available for the general public for decades, but with the commercial availability of VHR satellite images (e.g., IKONOS-2 satellite in 1999, and QuickBird in 2001), the imagery prices went down and a mass market emerged. This situation favored the development of new integrated methodologies (e.g., GEographic Object Base Image Analysis – GEOBIA) and new application fields, which had previously been the domain of airborne remote sensing and could now be tackled by satellite remote sensing (Moeller and Blaschke, 2006; Blaschke, 2010). However, methodologies such as segmentation, edge-detection or feature extraction had already been applied in remote sensing image analysis for decades (Blaschke, 2010).

The GEOBIA then emerged as a new alternative to the pixel-based classifiers. Although sometimes there may be objects with the size of one pixel, the applications typically seek to identify elements that are composed of multiple pixels such as roads, buildings, crops, etc. These applications require the classification of groups of contiguous pixels that are a part of an element. This leads to a new concept of classification, where pixels are grouped into objects based on information available from spectral, textural, contextual and spatial domains (Blaschke and Strobl, 2001).

The increased spatial resolution availability, allowed satellite imagery to become an alternative to aerial photography as high detailed source of information of the territory’s surface. The concatenation of 1) an increasing amount of image data being produced in an ever broader range of spatial, spectral, radiometric and temporal resolutions, 2) the orchestrated supranational programs and systems for regular or on-demand surveys of the Earth's surface (e.g. Global Earth Observation System of Systems - GEOSS, or the Global Monitoring for Environment and Security - GMES), and 3) the availability of powerful, off-the-shelf software that bridges image processing and GIS functionalities in an object-based environment, have made the GEOBIA an area of research possible (Blaschke, 2010).

1.2.3 URBAN REMOTE SENSING APPLICATIONS

Remote sensing data is widely used when geographic information is required. Areas of application include forestry, agriculture, climatology, oceanography, geomorphology, etc. When it comes to the urban environment, the applications described in the literature can be grouped, according to their purpose, in mapping processes or quantification processes.

The following lines of investigation address the most common applications of remote sensing in urban context, whose main goal is to classify and map the surface:

- Identify and classify land use and land cover (Herold et al., 2002; Caprioli and Tarantino, 2003; Misakova et al., 2006);
- Land cover change detection (Goetz et al., 2003; Bailloeul et al., 2005, Bianchin and Bravin, 2004);
- Urban green area mapping (Irani and Galvin, 2002; Mathieu et al., 2007, Zhang and Feng, 2005);
- Site suitability analysis (e.g., roads, dumps, communication networks) (Ramalingam and Santhakumar, 2000; King and O'Hara, 2002; Giap et al., 2003).

The following studies can be representative of those applications whose final goal is to quantify the properties of the surface:

- Mapping sealed areas for runoff estimation (Trauth et al., 2001; Bauer et al., 2004; Sawaya et al., 2003);
- Analyzing flood risk and damage assessment due to natural catastrophes (Taubenböck et al., 2006; Van der Sande et al., 2003; Sakamoto et al., 2004);
- Calculating taxes or subsides based on field structures (Argerich, 2004; European Commission, 2005; Carlee and Wolff, 2005; Jain, 2008);
- Evaluating urban sprawling (Herold et al., 2001; Viet et al., 2006; Moeller, 2005; Jat et al., 2008);
- Verifying legislation compliance (Karathanassi et al., 2003, Purdy, 2009)
- Estimating urban population (Souza et al., 2002; Herold et al., 2005a; Ramadan et al., 2004).

Several research projects/programs, that use remote sensing data for urban applications, are described in the literature. Based on its relevance, the following projects stand out:

- **SPIDER** Project (Improving SPatial Information extraction for local and regional DEcision makers using very high resolution Remotely sensed data), funded by the Belgian Science policy, between 2002 and 2005. The project aimed at improving spatial information extraction for local and regional authorities using VHR data, and to develop prototype versions of products with added-value that fulfill some of the actual information needs, as expressed by Belgian authorities. The projects achievements included: 1) a report based on a survey made to the representatives of local and regional authorities, for the assessment on their needs in geographic information; 2) a workflow for building Digital Surface Models and orthoimages from IKONOS data; 3) semi-automatic strategies to extract land cover classes in urban context form QuickBird images; and 4) mapping techniques for land cover extraction based on high and very-high resolution data combination (http://www.vub.ac.be/spider/);
- **MURBANDY/ MOLAND** Project (Monitoring Urban Dynamics/ Monitoring Land Use Changes), financially supported by the European Commission (EC) and the Joint Research Centre (JRC), was initiated in 1998 with the aim of providing a spatial planning tool that could be used for assessing, monitoring and modeling the development of urban and peri-urban environments. Until now, the MOLAND methodology was applied to an extensive network of cities and regions, covering a total of 50 000 km^2 (http://moland.jrc.it/);
- **EURMET** Project (Urban Sprawl of Major Cities in South West Europe), funded by the EC, between the period 2003-2006, aimed at characterizing the peri-urban areas of 10 European cities, using context information and spatial structure (http://www.interreg-sudoe.org/);
- **GMES** Program, is an initiative of the European Space Agency (ESA) and the EC for responding to a number of European directives and policies. The program aims to support users across Europe in their efforts of fulfilling their reporting and management obligations in an improved way. Land geo-information services are based on general geo-information on Land Cover and Vegetation created from EO data which is harmonized and standardized, allowing cross-border applications and

comparisons. The first phase (2003-2005), called GMES Urban Services, was intended to demonstrate a portfolio of products derived from satellite imagery and other sources in cooperation with a group of users (cities and regional authorities). Among others, large scale land use maps, land use change maps and monitoring of urban planning, were contemplated. Phase two (2005-2007), called GSE-Land, addressed among others, the European Urban Atlas. This mapping service offers a collection of land use maps of the main urban areas in the European Union (EU) with more than 100.000 inhabitants. It offers reliable and comparable urban planning information delivered through GMES. More than 300 maps of major cities will be available by 2011. The Urban Atlas has potential applications in several fields, including a deeper understanding of climate change, and offers a sound basis for calculating spatial statistic and the revision of urban plans. The methodology used to extract information included image segmentation, classification and visual interpretation (http://www.gmes-gseland.info/);

- **UDR** program (Urban Dynamics Research), funded by the United States Geological Survey (USGS) studies the landscape transformations induced by the growth of metropolitan regions over time, in the USA. Retrospective urban land use databases, that reflect several decades of change, were produced using sources such as historical maps, aerial photographs, and Landsat satellite data. These databases were then used to analyze the effects of urbanization on the landscape, and to model urban growth and land use change under alternative growth scenarios. The databases developed by the UDR program contain interpretations of urban extent, transportation routes, water features, and other important land uses, for use in GIS. Digital animations are available to help visualize the temporal patterns inherent in the data, as well as land use change models and further documentation (http://landcover.usgs.gov/);
- **100 Cities** Project, is a National Aeronautics and Space Administration (NASA) funded program to collect satellite-based remote sensing data from 100 cities around the world in order to support socioeconomic and bio-geographic comparisons and to build collaborations among urban practitioners and scientists. Initially, the program was based on Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images (with 15 m spatial resolution). The program collected and analyzed daytime and nighttime ASTER images from 100 urban centers, twice a year, to obtain winter and summer information. Each urban centre was then

characterized trough land cover classification, done at the pixel level by an expert system. Based on these land cover maps, metrics were extracted to allow global comparison of all cities. For the 100 cities, the effects of urbanization were compared, and standardized urban remote sensing data sets were made available for the international community. This included temperature, vegetation, land classification, and social data. More recently, the program was redefined, and a greater amount of remote sensing data was contemplated (Moderate Resolution Imaging Spectroradiometer - MODIS, Landsat, aerial photography, etc.) to characterize and model the urban development trends and the resilience to natural environmental threats. The main results of the project to date include the development of knowledge-based and object-oriented LULC classification algorithms that are generally applicable to all urban centers (http://100cities.asu.edu/).

Based on the projects mentioned above, one notes a growing interest in using satellite images with spatial resolutions compatible with the study of urban areas. These images seem to be replacing aerial photographs as a source of information in applications whose purpose is the classification of land surface by visual analysis (e.g., Project MURBANDY/MOLAND). On the other hand, automatic processing is emerging as an alternative to the manual process (e.g., Project EURMET).

1.3 THEMATIC LAND USE AND LAND COVER MAPS IN PORTUGAL

There are many sources of information on LULC in Portugal, varying in scale, nomenclature, date, and data source. This section is intended to summarize the most important cartographic sources available in mainland Portugal, identifying products at national and regional levels, and some maps produced under research projects.

Portugal has available for the national level, two LULC maps: the Land Cover Map of Portugal (*Carta de Ocupação do Solo* - COS) and the CORINE Land Cover (CLC). These two maps are free and available to the general public. For more limited areas, there is the Urban Atlas (for Lisbon, Coimbra, Braga, Aveiro, Setúbal and Faro). With a more limited availability, there is the Land Use Map of Lisbon Metropolitan Area (CARTUS-AML), the Land Cover Map for the District of Évora, and the cartography produced by the projects EURMET (for Lisbon and Oporto) and MURBANDY/MOLAND (for Oporto, Setúbal and the Algarve). In addition to these maps, there are other mapping products that are not described here because their scale is small (< 1:100 000) (e.g., National Forest Inventory) or because the nomenclature does not describe in detail the urban environments (e.g., Land Cover Map 1995 for Algarve). It is also excluded from this analysis, the cartography produced in the framework of the Master Plan (*Plano Director Municipal* – PDM), given the great variability existing in the 308 municipalities.

The **CLC** map was produced for mainland Portugal, in the framework of the European project CORINE. The CLC reports the inventory on land cover, at a scale of 1:100 000, using 44 classes at level 3 of the CORINE nomenclature. The technical characteristics are: vector model, with minimum unit of 25 ha and minimum spacing between lines of 100 m. The CLC methodology is based on visual analysis of satellite imagery, using ancillary information. The first version dates from the 1990's. In 1999, the European Environment Agency (EEA) and the JRC launched the IMAGE and CORINE Land Cover 2000 (I&CLC2000) project with the main goal of updating to 2000, the existing CLC mapping and to collect information on the land cover changes in Europe that took place between the two dates (1990-2000). The change detection process and the mapping of the land cover changes was carried out by means of image comparison, using computer assisted image interpretation tools. Among the 44 classes available in CLC's more detailed level, 11 correspond to classes of urban land use and land cover. The Overall Accuracy of the thematic mapping CLC2000 for Portugal, on the 3^{rd} level of nomenclature, was 83% with a confidence interval of 80.47 to 85.20 (Painho et al., 2005). Presently, three CLC maps are available for Portugal: CLC1990, CLC2000 and CLC2006. Furthermore, there is also two Land Cover Changes, over the period 1990-2000, and 2000-2006, with a minimum mapping unit change set to 5 ha.

The **COS** from 1990 (COS90) was produced by the National Centre for Geographic Information (CNIG), now integrated into the Portuguese Geographic Institute (IGP), together with the Pulp Producers Association (*Associação das Empresas Produtoras de Pasta de Celulose*), currently the Paper Industry Association (*Associação da Indústria Papeleira*). The map was created by visual interpretation, followed by on-screen digitizing of aerial photography in color infrared film, obtained in the summer of 1990. This project consisted in obtaining graphical and numerical information on the land cover in mainland Portugal, resulting in a product with a 1: 25 000 scale and a minimum mapping unit of 1 ha. The COS'90 nomenclature was established to support forest planning and management, and is organized in five hierarchical levels. This *a* *posteriori* classification system, while allowing greater adaptation of the nomenclature to the reality, leads to a high number of classes. It presents 78 classes of LULC that can be combined with additional information (e.g., forest density) to produce a classification code for each homogeneous zone. The legend provides a variety of combinations between different types of coverage, totaling more than 800 different classes. Still, 33 classes of urban LULC in the 5th level were identified. However, in 1998, only 50% of the territory was covered, and more recently were released more mapped areas, including those covering the municipalities of Cascais and Sintra. As for the values of accuracy, there is no reference to the quality of this map. Nowadays, a new version - the 2007 version (**COS2007**) – is being produced, based on orthoimages, derived from aerial coverage produced by the Forest Institute (*Direcção Geral de Recursos Florestais* - DGRF) and IGP for 2004, 2005 and 2006. It is expected this new version for the end of 2011. This new version no longer includes the discrimination of the cover degree, and thus is limited to 192 classes in the most disaggregated level, i.e., it changed for an *a priori* classification. The urban use is represented by the level 1 class "Artificial areas" and is divided into 33 subclasses, at level 5.

A Land Cover Map for the District of Évora was produced by the Association of Municipalities of the District of Évora, using the 2004 orthophotos from DGRF/IGP. The mapping process was based on visual analysis at a 1:10 000 scale and minimum unit of 0.5 ha. The nomenclature resulted from an adaptation of the CLC nomenclature for the map scale. The most disaggregated level provides nearly 95 urban classes (Guiomar et al., 2006).

The **CARTUS-AML** map is another project on urban land use mapping, developed for the Lisbon Metropolitan Area. The information was obtained by computer-assisted visual analysis of vertical aerial photographs from 1991, orthophotos and satellite images of medium resolution (SPOT XS and Landsat TM), at 1:25 000 scale, a minimum unit of 0.5 ha, and 15 classes, 7 of which relate to land use in urban areas. These were determined according to the temporal dimension of the project, the detail and accuracy required, and as always, the resources available. The process of validation was based on a visual evaluation using orthophotos (Tenedório et al., 1999).

The **Urban Atlas** contains information derived by visual interpretation mainly of EO data with support by other ancillary data, for the cities of Coimbra, Braga, Lisbon, Setúbal, Aveiro and Faro. The urban classes are available with a minimum unit of 0.25 ha, 1 ha for other classes (agriculture, forests or semi-natural areas, wetland and water), and minimum spacing between lines of 10 m, at 1:10 000 scale. For the six Portuguese cities, a map for 2007 is available. The EO data used was from the Advanced Land Observing Satellite (ALOS) sensor, with 2.5 m resolution, and the map had an Overall Accuracy of 85.2% for the city of Lisbon (Meirich, 2008). Furthermore, any data model of the Urban Atlas is, in a higher level of aggregation, compatible with the CLC.

The **EURMET** project produced two maps for Portugal: one for the Metropolitan Area of Lisbon and another for the Metropolitan Area of Oporto. The maps were produced by object oriented analysis of SPOT 5 images, from 2004, according to a model compatible with the CLC nomenclature. The nomenclature was sub-divided into four levels of detail, being identified, in the 4th level, 10 categories of urban LULC. Global estimates of accuracy in the first level, for all cities, are of 70% compliance (Albert, 2005).

The **MURBANDY/MOLAND** cartography includes the city of Oporto, the Peninsula of Setúbal and part of the Algarve region (between Vila Real de St. António and Albufeira). For each area, a LULC map was produced, with a minimum unit of 1 ha for urban areas and up to 3 ha for rural areas, at 1:25 000 scale, for the reference year (1997 for Setúbal and Oporto and 1998 for the Algarve) and for historical dates. The proposed nomenclature was based on the CLC nomenclature, with a more detailed fourth level for artificial areas that identified 10 categories of urban LULC. All maps were obtained by visual analysis of aerial photographs and orthophotos and one high spatial resolution panchromatic image of the Indian satellite IRS-1C, with 5.8 m resolution (Caetano et al., 1999). However, the MURBANDY cartography has no associated quality information.

Since the object of study is the use of geographic information for local applications, the LULC maps included in the PDM's framework, although not within the scope of national program or investigation project, are also presented in this section.

At the municipal level, the LULC classes used in the PDM are defined by law. In the 1st generation of plans, the classification system was defined by the Law 69/90, March 2, which mentioned that classes should be defined based on the dominant use: “built-up”, “urban”, “industrial activity”, “extractive industrial activity”, “agriculture”, “forestry”, “cultural and natural”, and “vacant land” for future infrastructures. This decree was later repealed by the Law on Spatial Planning and Urbanism (Law 48/98, August 11) and the Decree Law 380/99, September 22. The land was then classified into “urban” and “rural”. The urban land includes “urbanized areas”, “land set aside” for construction and “land allocated to the ecological structure”, while the rural land includes “forest” and “agricultural areas”, the “mining areas”, the “industrial activities”, the “natural spaces” and “infrastructure” that do not involve classification as urban land. This new classification appears in the 2nd generation of PDMs that is now being completed.

The LULC maps available for Portugal described in this section, use different nomenclatures, vary in detail and scale. With the exception of the CLC2000 and the Urban Atlas maps, the values of thematic accuracy of these maps are unknown. Table 2 provides a summary of the technical specifications of maps described in this section, leaving the cartography produced under the PDM’s framework, since it is not a standard product.

Table 2. LULC maps available for Portugal, with 3 or more urban classes in the nomenclature

Map	Year	Scale & Min. Map Unit	Nomenclature	Source data	Method	Coverage	Accuracy assessment
CORINE Land Cover (CLC)	1990	1:100 000 25 ha	3 Levels 44 Classes	Landsat MSS Landsat TM	Visual-analysis	Portugal mainland	Not performed
	2000	1:100 000 25 ha	3 Levels 44 Classes	Landsat ETM+	Visual-analysis	Portugal mainland	Overall Accuracy of 83% in the 3rd level
	2006	1:100 000 25 ha	3 Levels 44 Classes	SPOT4 HRVIR SPOT5 HRG IRS-P6 LISSIII	Visual-analysis	Portugal mainland	In production
Carta Ocupação do Solo de Portugal Continental (COS)	1990	1:25 000 1 ha	5 Levels	Aerial photograph on paper	Visual-analysis	Portugal mainland (incomplete)	Not performed
	2007	1:25 000 1 ha	5 Levels 192 Classes	Orthophoto	Visual-analysis	Portugal mainland	In production
Carta Ocupação do Solo do Distrito de Évora	2004	1:10 000 0.5 ha	5 Levels 94 Classes	Orthophoto	Visual-analysis	District of Évora	Not performed
Urban Atlas	2007	1:10 000 0.25 ha	4 Levels for the Urban areas 19 Classes	ALOS	Visual-analysis	Lisbon, Coimbra, Braga, Aveiro, Setúbal, Faro	Overall Accuracy of 85,2% at the 4th level (Lisbon map)
Project EURMET	2004		4 Levels 18 Classes	SPOT5 HRG	Automatic classification	Lisbon and Oporto Metropolitan Areas	Field survey
Project CARTUS-AML	1991	1:25 000 0.5 ha	15 Classes	Landsat TM SPOT XS	Visual-analysis	Lisbon Metropolitan Area	Qualitative analysis

CONCLUDING REMARKS

This chapter described the urban environment and showed that remote sensing data can potentially provide information on human settlements. Although the interpretation of aerial photography remains a standard procedure for mapping and monitoring the LULC and its changes (Hansen, 2003, Jensen et al., 2005), the improvement of technologies provided an opportunity for the development of applications of satellite imagery in urban areas. However, these data sources will only be useful for land management activities if they provide information on urban characteristics such as (Donnay et al., 2001):

- The location and extent of urban areas;
- The nature and spatial distribution of different classes of land use within urban areas;
- The network of transport and associated infrastructure;
- Census indicators;
- The 3D structure of urban areas for telecommunications (areas of inter-visibility) and environmental assessment studies and;
- The monitoring of changes in these characteristics over time.

To meet these requirements, a series of questions or assumptions must be analyzed. The measure of compliance with these assumptions, will dictate the success of applications of remote sensing data in urban areas.

Given these considerations, and the fact that remote sensing data is the primary source for assessment of LULC patterns in the landscape, in order to understand, monitor, model and manage human interaction with the environment, three components are required (Hay et al., 2003):

- Remote sensing data with fine spatial, temporal and spectral resolutions, and covering a geographical extent sufficient to access the multi-scale patterns of the landscape;
- Theory and methods capable of identifying the pattern of occurrence of different objects of the real world;
- Ability to link and query these objects within an appropriate hierarchical structure.

2. METHODOLOGICAL APPROCHES FOR LAND COVER MAPPING WITH REMOTE SENSING DATA

Information about the LULC is essential in any planning activity or land management action. Such characterization of the surface is usually presented as a thematic map. The most common way to produce LULC maps is using images, in analogue or digital format, collected by airplane or satellite, as primary data source. Regardless of the imagery source, there are a set of essential steps in any mapping project based on EO data:

– Statement of the Problem

  The goals of the project must be expressed: the thematic classes to be mapped, the most suitable scale, the period under analysis, and the area of interest (e.g., large-scale mapping of buildings in the city of Lisbon, for 2007);

– Selection of the EO data

  The characteristics of the remote sensing data that are able to fulfill the project's demands have to be decided (e.g., VHR image). Afterwards, the availability of images for the period of analysis or the need to program new acquisitions must be investigated. Also the identification of collateral data to use (e.g., elevation and/or census data) occurs in this stage. Such ancillary data may be used in any stage of the project (e.g., photos for documenting land use classes, agricultural calendars to determine the dynamics of classes, or Global Positioning System – GPS - data for positional accuracy assessment);

– Selection of an appropriate processing methodology

  The pre-processing phase where the geometric and radiometric correction of images takes place in order to correct possible distortions, to assign a coordinate system and to remove or reduce atmospheric effects, is the first step in data analysis. Afterwards, through photo-interpretation or semi-automatic methods, information is extracted from the images and presented in the form of a thematic map. This is usually the longest phase in the project life cycle;

– Accuracy assessment of the final map

  The final phase involves verifying how the map produced according to its specifications, is representative of reality, by generating accuracy reports and quality indices, and suitable reference data.

Based on these general steps, the next sections describe the methodological aspects involved in the design of a LULC mapping project using digital remote sensing images.

2.1 SELECTION OF THE BASE MAP AND THE MAP SCALE

The base map is the geographic reference document for mapping. It is usually a map with information on the topography, main transport routes, rivers or lakes, relief, or administrative boundaries. The purpose of this base information is to provide an accurate representation of the reality to support engineering works, projects and planning actions in the territory. There are three common types of base-maps: planimetric maps (e.g., building footprints), orthophotos, or other large-scale maps (e.g., street maps or maps depicting the terrain) (Figure 7).

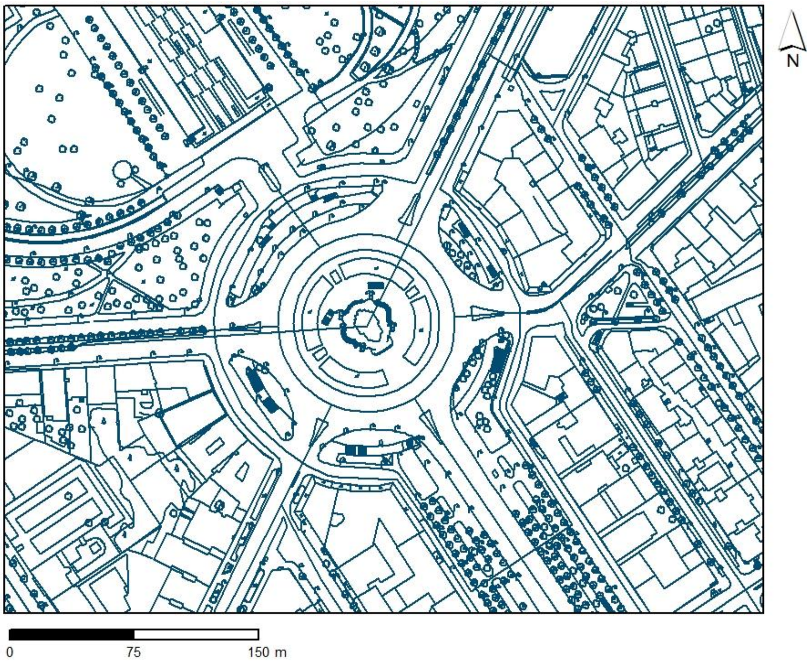


Figure 7. 1:1 000 Planimetric map of Lisbon city

When establishing the base map, the working scale has to be selected also. This is a difficult task because not every user needs the same level of detail or accuracy. Natural resources managers generally require less accurate maps than engineers and public utility planners. Furthermore, the cost of map production increases with the scale detail.

The scale indicates the detail of information represented, and must take into account the size of the smallest object to be mapped (the minimum mapping unit), and the density and diversity of the details of the surface under analysis. In this context, there are several concepts of scale and may even exist different interpretations. Lam and Quattrochi (1992) summarize some of the most common connotations of scale:

– Cartographic scale or map scale

  It is understood as the ratio of a distance on the map to the corresponding distance on the ground. Consequently, large scale maps provide more detail on the mapped surface than small scale maps. Scale can be regarded as the most important geometric transformation that the geographic information is submitted to;

– Resolution

  It is the size of the smallest distinguishable spatial element. It is usually linked to area units, and is a term widely used in remote sensing, where the intrinsic form of satellite images is a regular square grid (matrix format). The resolution of a sensor determines its ability to distinguish objects on the Earth's surface, so the higher the resolution of a sensor, the greater the detail of information captured. If a SPOT image is under analysis, its resolution of 10x10 m means that objects that fall below that value will not be correctly represented in the image, even when zoomed;

– Geographical scale

  It refers to the spatial extent of the study area. A major field of study is thus a large geographical scale. The larger the geographical scale, the lower the applied map-scale;

– Operational scale

  Refers to the extent to which the phenomena occur. A city operates on a scale larger than the building.

The two initial concepts, map scale and resolution, have a precise numerical definition, leaving no room for doubt as to their employment. But in the following concepts, there is a reasonable subjectivity. It is difficult to establish a good definition of what is a large or small map scale, for a given occurrence. The concept of scale in digital cartography is somewhat ambiguous. Indeed, the term applies to cartographic representations on paper, where the size does not vary. But in a digital environment or in a GIS, there is the possibility to zoom to the data. However, in a GIS, zooming in or zooming out on a small scale does not increase the level of detail. Consequently, this capacity of handling means that the concept of "map scale" does not apply, strictly speaking, to geographic information in a digital environment. In this case, the term refers to the detail of the data source. Still, and as the detail of a digital map depends on the detail of the spatial data that was in its origin, it remains true that a large-scale digital map is more detailed and specific than a map of smaller scale.

Another factor to take into account when selecting the map scale is the complexity of the environment to be represented. The urban environment is spatially complex as a result of the high heterogeneity of the materials that make up the surface. These are characterized by a mixture and an non-systematic distribution of natural and artificial land cover classes. Depending on the scale of observation, the processes that seem homogeneous at small scales may become heterogeneous at higher scales. This indicates that some processes are scale-dependent, changing its interpretation from a scale to another (Stone, 1972). Consequently, the results are specific to a given scale, and the conclusions drawn from a scale and extrapolated to others may be incorrect (Foody and Curran, 1994). Therefore, the choice of the map scale is dictated by its use and base data, and it will determine the perception of the area to be mapped.

Small (2003) studied the scales of urban reflectance through spectral mixtures analysis of IKONOS images. Spatial autocorrelation analyses, performed with the panchromatic band, provided a quantitative measure of the characteristic spatial scales of urban features. The analyses of 6357 sites in 14 urban areas indicated that the characteristic scale of urban reflectance was consistently between 10 and 20 m for the cities in this study. These results explain why urban areas are spectrally heterogeneous when captured by medium-resolution sensors (e.g., 20-30 m).

Coupled with the choice of the working scale, is the level of simplification of the information to be represented in the base map. The selection of the map elements should be sufficient to allow the location and perception of the geographic area in question. All the basic elements should be collected at the same level of generalization in order not to mislead the map's user.

Finally, it is also important to consider the detail of the thematic information and of the base information theme itself. It is not correct to represent the thematic map information in greater detail than the basic information, because the user can be mislead, giving the idea that the theme has more detailed information than it has in reality (Robinson et al., 1995).

2.2 CLASSIFICATION SYSTEM

A primary component of LULC mapping is describing spatial phenomena through categorization into classes. This is usually done by adopting or developing a classification schema. In the thesis context the terms classification system and nomenclature are used as synonyms. The data classification is an abstract description of a real situation through the use of well defined criteria. Sokal (1974) defined it as the "ordering or arrangement of objects into groups, or sets, based on their relationships". A classification system describes the systematic structure with the names of the classes and the criteria used to distinguish them. It is often present in the form of a list of categories, summarizing information in a highly reduced form while attempting to maintain maximum information content. The end-product is a list of names and descriptions linked by one-to-one mapping correspondence and generally presented according to the structure of the classification so-established;

The classification system can be presented in two formats: hierarchical and non-hierarchical. Most systems are hierarchical because it offers greater consistency and ability to incorporate different levels of information, starting with a structure of more broad classes, which are subdivided into more detailed ones. In each level, classes are mutually exclusive. Rules must also be established in order to guide the objects' classification according to predefined criteria. These types of procedures facilitate the classification repeatable and the implementation of generalization processes over the thematic and cartographic information.

Food and Agriculture Organization of the United Nations FAO (2005) mentions two kinds of data classification: *a priori* and *a posteriori.* In the first case, the classes are defined conceptually, before the data collection. This method has the advantage of producing a classification independent of the study area and of the methods for data collection. However, it is a rigid method that can hamper the correct allocation of areas to the pre-defined classes. The classification *a posteriori* is a direct approach, and is based on analysis of data collected after the event. Its advantage lies in the flexibility of adapting the legend to the site. However, this kind of approach is very oriented towards the study area in question, and difficult to apply in areas with distinct characteristics.

2.2.1 THE CONCEPTS OF LAND USE AND LAND COVER

Together with the detection, the identification of urban elements is a vital process to the successful usage of remote sensing data in land planning. The identification of urban elements requires a study of its structural features, which include notions of continuity and discontinuity, single and multi-family housing, suburbs, urban fringe, outlying areas, etc. These classes must be well documented in the classification system.

These questions refer to an additional "difficulty" when classifying urban objects: images collect spectral information, allowing classification of the land cover, but what really matters to the planners is the land use. The word “cover” refers to physical materials that constitute the Earth's surface (e.g., grass, water, concrete, etc.), whereas “use” refers to human activity occurring on that surface (e.g., residential, commercial, industrial) (Barnsley and Barr, 2000). The terms cover (land cover) and use (land use) are recurrently applied as synonyms and used in the same classification scheme (e.g., the CLC nomenclature).

When analyzing EO images, it is generally easy to make the relationship between the land cover and spectral reflectance. However, the same is not true for the land use. The concept of use is an abstract concept, resulting from the fusion of social and economic factors that often can not be inferred directly from spectral analysis. In addition to the morphological properties and the spatial relationship between regions of land cover, other indicators are needed to identify the land use. Characteristics as the proportion of different types of land cover, density of buildings, or proportion of sealed surface, can help to move from cover to use. Figure 8 illustrates the relationship between land cover and land use.

Zhan (2003) suggested extracting information on land use, using satellite imagery classification in sequential levels: land cover classification, definition and delineation of land use units, and its classification. Three types of hierarchical objects were outlined: fundamental objects at pixel level, land-cover objects at the land cover level and land-use objects at the land use level.

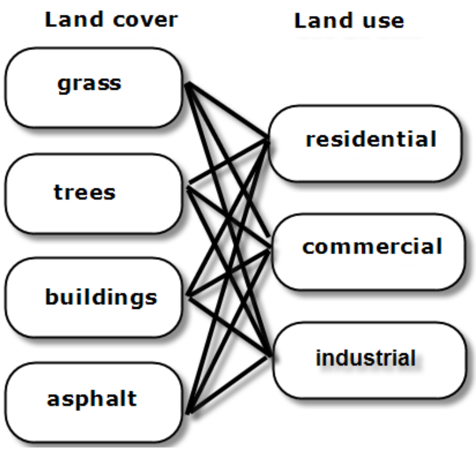


Figure 8. Many-to-many relation between land cover classes and land use classes (adapted from Fisher et al., 2002)

Many classification systems have been developed and proposed in different countries. The following sections present the most relevant ones, with emphasis on urban classes.

2.2.2 International Classifications Systems

In 1971, it was created in the **United States** the Steering Committee on Land Use Classification and information to develop a classification system for national maps obtained from remote sensing data (aerial photography or satellite image) and that would meet different levels of detail (national, regional and local). The classification system developed by Anderson et al. (1976) is organized into four hierarchical levels that reflect the detail possible to obtain with different sensors (e.g., level 1 is intended to maps produced with Landsat MSS, at a scale of 1:100 000, or lower). Levels 3 and 4 correspond to scales greater than 1:20 000, and therefore the most suitable to classify the land cover at municipal or local level. Although the system has four levels, only levels 1 and 2 are specified by the USGS. Levels 3 and 4 are defined by users, according to the application in question, but following the assumption that the classes in each level must be aggregated into higher categories.

At **European level** two classification systems stand out. The CLC nomenclature is used for LULC mapping and monitoring at the scale 1:100 000. This classification system is organized in three hierarchical levels, which includes 44 classes in the most disaggregated level. The class "Artificial surfaces" (level 1) is subdivided into 11 classes in its more detailed level. The concept of continuity is used to specify the class "Urban fabric" (level 2) into "Continuous urban fabric" and "Discontinuous urban fabric" (level 3).

Another classification system, also available for **Europe**, is the Classification for Land Use Statistics: Eurostat Remote Sensing Program (CLUSTERS). This nomenclature was implemented in 1993, and is used by the Eurostat for urban and rural areas statistics. The CLUSTERS is organized into four levels, up to 60 classes of LULC in level 4. The level 1 class "Man-made areas" is divided into 23 classes at level 4. The detail of the discrimination is based, in some classes, in terms of density and continuity (e.g., class "Continuous residential areas of moderate density").

In **England** the National Land Use Database (NLUD) uses a classification system that has been suffering successive improvements, and is now in version 4.4. Level 1, includes 13 classes while level 2 describes 41 classes. This classification system was developed with three objectives: (1) establish a national system to classify and define groups of LULC elements, (2) provide consistent national databases to identify, store and report the LULC, and (3) provide a standard for the institutions responsible for collecting such data. Level 1 class "Residential" is subdivided into 3 more detailed classes in level 2.

The **Netherlands** has its territory covered by the Land Use Database of The Netherlands (LGN). The LGN describes the land use in three levels, with a total of 39 classes in its most disaggregated level. The LGN is more suited to describe the natural environment, and the urban classification depends on the type of vegetation or the environment where it is (e.g., "Build-up in rural areas" or "Coniferous forest in urban areas").

Australia has the Australian Land Use and Management Classification (ALUM), which defines a consistent method of collection and presentation of information on the land use for a wide range of users. The 6th version dates from 2005 and follows a hierarchical structure that describes the land use according to the degree of intervention or potential impact on natural resources. The class "Intensive Use" (level 1) is subdivided in 3 classes and 22 subclasses that describe the urban environment.

In **Portugal** there are maps that describe both the land use and the land cover based on remote sensing data (aerial photography or satellite image). At the national level, there are two classification systems, used in the two LULC maps available for the country: the COS' and the CLC, already presented in chapter 1.

2.3 DATA SELECTION FOR LARGE-SCALE MAPPING

Of all imagery users, cities typically require geographic information at the largest scale and the highest level of resolution, due to the more intensive land use and the density of the population and the built environment. An obvious source of spatial information of the Earth's surface is the imagery collected remotely. The main advantage of such imagery is that they provide a realistic picture of the terrain, presenting details that are difficult to illustrate through manual cartography.

2.3.1 VERY-HIGH RESOLUTION IMAGERY

In general terms, aerial imagery refers to photography or digital pictures taken from the air. Traditionally, aerial photos have been the main source about the Earth's surface over the last 100 years (Short, 2010). Consequently, aerial photographs are the most widely used source of data for mapping land cover at large-scale (Redweik, 2007). This is mainly because the acquisition of aerial photography is a method already well established, and used for decades. Of fundamental importance to the quality of aerial imagery is the camera used to obtain the images. There are two broad types of airborne cameras: film-based and digital cameras. The most common are film-based, single-lens frame cameras, with lenses of high geometric quality to minimize distortions (Morgan et al., 2010). Digital cameras, on the other hand, use electronic sensors to record reflectance, and store it digitally instead of on film.

The capture of aerial images allows, according to the height of the flight and the characteristics of the lenses/sensors, collecting data with very high geometric resolution. Aerial images taken for topographic purposes are typically imaged with a 55-65% overlap along the flight line and 15-35% sidelap (IGP, 2006), allowing stereoscopic viewing. Still, aerial images are not a product readily suitable for mapping. Aerial images are created using a central or perspective projection. Consequently, the relative position and geometry of the objects shown depends upon the location from which the image was taken. This fact is responsible for the occurrence of distortions and displacements in aerial images. Both distortion and displacement cause changes in the apparent location of objects in images. For thematic mapping, a procedure to correct for geometric displacements and provide spatial reference, called orthorectification, is generally applied. Orthorectification is one of the most important methods for preparing fundamental data for multi-sensor integration applications. Orthorectification transforms the central projection of the image into an orthogonal view of the ground with uniform scale, thereby removing the distorting effects of platform tilt and effect relief displacement.

Due to technological advances, sensors are increasingly able to capture more distant objects. In 1972, the first satellite designed for EO was launched. The image was captured by digital sensors rather than by photographic films. However, the construction of satellites implies a compromise between spatial resolution and the amount of spectral information, at a given altitude, that can be collected by the sensors. But, to map LULC at local scales (e.g., 1:10 000), both high spatial and spectral resolutions are needed. Traditionally, aerial photographs fulfill these two demands: spatial resolutions in the order of centimeters and information in various ranges of the electromagnetic spectrum (visible and near infrared). But the same was not true for early EO satellites. Initially, the sensor MSS, aboard Landsat 1, recorded the electromagnetic radiation in four spectral bands (green, red and two infrared bands), and with a spatial resolution of 80 m. These characteristics only allowed mapping the surface at national scales (e.g., 1:500 000). However, the fact that the Landsat program, an initiative of the USGS and NASA, is active since 1972, capturing images from around the planet, in a systematic, consistent way and with increased quality, and at the same time at a reasonably price, potentiated the development of methods for classifying their data into information.

Along with the commercial availability of satellite images, there was also a big investment in models for georeferencing, for radiometric correction, for image classification and statistical models for evaluating the quality of the products generated from satellite images. These scientific developments have been also accompanied by the acquisition of images with higher spatial resolution (but with few spectral bands) and the development of hyper-spectral sensors (but with coarse spatial resolutions):

– Advanced multispectral sensors called hyper-spectral sensors, detect hundreds of very narrow spectral bands throughout the visible, near-infrared, and mid-infrared portions of the electromagnetic spectrum. Their very high spectral resolution facilitates fine discrimination between different targets based on their spectral response in each of the narrow bands, but they do it with medium/low spatial resolutions. These images are used to study geology, environmental monitoring or high-precision agriculture;

– Sensors designed to capture high spatial resolution images (e.g., OrbView with 0.50 m in panchromatic mode), do it with low spectral resolution (three bands in the visible and one in the near infrared). These latest generation of sensors developed for spaceborne platforms, already allow capturing images with similar characteristics to the ones captured by aerial cameras. These new satellite images are aimed at higher-scale studies such as the study of urban environment. Many sensors have a combination between higher spatial resolution panchromatic channel and lower resolution multispectral channels.

The choice of imagery is then directly related to the map's purpose. In fact, for local scale mapping, images with high spatial resolution (e.g., IKONOS or QuickBird) are a common choice. To represent the surface at regional scales, selection of SPOT and Landsat images is usual, while lower scales generally use National Oceanic and Atmospheric Administration (NOAA) or SPOT-VEGETATION images. Since the subject of this thesis is urban mapping, the type of imagery to be explored is of very high-spatial resolution. VHR imagery is classified based on four characteristics: spatial, spectral, radiometric and temporal resolution. The higher the spatial resolution of the imagery, more man-made objects can be identified. In VHR imagery, features from individual urban structures, like buildings, can be identified based on the context in which each building is located, with easy detection, for example, of green areas, space between buildings, and distance from main transportation. Commercial VHR satellite images are now available at 0.50 m resolution, while aerial digital images can go up to 0.10 m (e.g., images from Digital Mapping Camera - DMC). Choosing the proper imagery basically depends 1) on the desired final map scale, and 2) on the sensor's characteristics that enable the mapping of the objects of interest. In fact, the use of bands storing non-visible and visible electromagnetic radiation provides additional dimensions that enable map makers to distinguish among various classes of objects. The radiometry is also important when extracting large-scale information. Having 11-bit images (2048 levels of grey), rather than 8 bits (256 levels of grey), allows more information in shadowy areas to be extracted, and ennables more precise spectral signatures, benefitting feature identification. Finally, the temporal resolution must also be addressed, since it is directly related with the updating rate. Regarding satellite data, the revisit rate for a given sensor, depends primarily on the off-nadir viewing capability, and secondly on cloud cover. In any case, applications that require multi-temporal observation with seasonal frequency can be easily carried out.

The development of applications for this type of imagers is very recent. In fact, until the early 1990s, the access to VHR image and surveillance technology was limited to a few countries (USA, Russia and China). Since then, France, India and Israel have acquired capacity in this area, and other countries have announced programs to develop this technology. In response to these developments, the government of the USA downgraded many of the hundreds of thousands of military satellite images, while also changed the licensing restrictions on commercial high resolution satellite systems. Table 3 describes some satellites currently operational, equipped with high resolution sensors (spatial resolutions greater than or equal to 1 m), and available to the general public. The former limitation of most often four color channels has been extended with eight color channels of WorldView-2. With GeoEye-2, planned for 2012, and Cartosat-3, planned for 2014, the spatial resolution even will be improved (0.25 m and 0.33 m in the panchromatic mode, respectively). Until now, for the satellites operated from the USA, a restriction to the resolution of 0.5 m exists. This is the reason why images from GeoEye-1 being collected with 0.41 m a pixel for nadir view, WorldView-1 with 0.45 m, and WorldView-2 with 0.46 m, are only delivered to general public with 0.5 m of spatial resolution. But this may change by the competition of Cartosat-3, an Indian satellite. Besides the announcement of images with resolutions down to 0.25 m, also with Pleiades 1 and 2, expected for 2011 and 2012, the number of satellites with 0.5 m resolution will be enlarged. Figure 9 presents two VHR images, with different spatial resolutions.

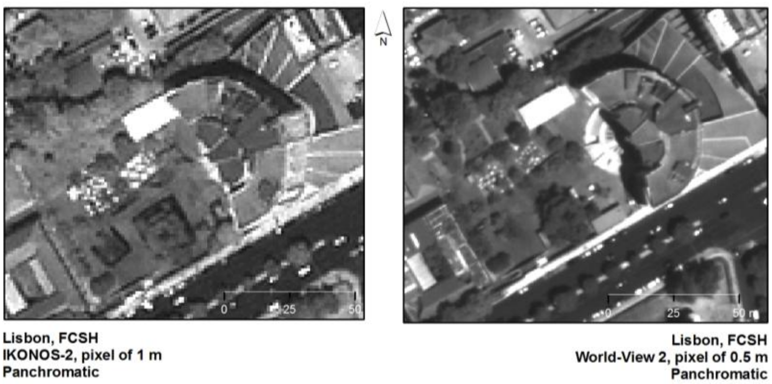


Figure 9. Different spatial resolutions for the same location

Table 3. Characteristics of the satellites currently in space that capture images with very-high spatial resolution

Satellite	Year	Spectral Res. (µm)	Spatial Res. at Nadir (m)	Radiometric Res. (bits)	Min. revisit time (days)	Cost ($/km^2)
IKONOS-2	1999	RGB, NIR Pan	4 (MS) 1 (Pan)	8-11	1	20.00 €
QuickBird-2	2001	RGB, NIR Pan	2.44 (MS) 0.61 (Pan)	11	1	29.00 USD
OrbView-3	2003	RGB, NIR Pan	4 (MS) 1 (Pan)	11	3	20.00 USD
KOMPOSAT-2	2006	RGB, NIR Pan	4 (MS) 1 (Pan)	10	5	15.00 USD
WorldView-1	2007	Pan	0.50 (Pan)	11	1.7	14.00 USD
GeoEye-1	2008	RGB, NIR Pan	1.65 (MS) 0.41 (Pan)*	11	2	25.00 €
WorldView-2	2009	RGB, NIR Pan Red edge, Coastal, Yellow, NIR2	1.84 (MS) 0.46 (Pan)*	11	1.1	29.00 USD

* note that imagery must be re-sampled to 0.5 m for non-US Government customers, NIR-Near-Infrared, MS–Multispectral, Pan–Panchromatic

2.3.2 Altimetric Data

The availability of digital data representing elevation is critical for performing geometric and radiometric corrections on remotely sensed imagery. It also allows the generation of contour lines and terrain models, thus providing another source of information for analysis. Such information can be generated in several ways. Other sources are based on remote sensing data. Methods include: 1) stereogrammetry techniques using air photos (photogrammetry), VHR satellite imagery, or radar data (radargrammetry), 2) radar interferometry, and 3) laser scanning.

Stereogrammetry involves the extraction of elevation information from stereo overlapping images. Interferometry involves the gathering of precise elevation data using successive passes (or dual antenna reception) of spaceborne or airborne SAR (CCRS, 2009).

The development of airborne laser scanning goes back to the 1970s, but only in the late-1980s kinematic GPS provided the necessary centimeter-level positioning accuracy required for high performance (Elaksher et al., 2002). Nowadays Airborne Laser Scanning (ALS) is one of the most frequently used methods for the acquisition of high precision topographic data. The principle of ALS – also known as LiDAR – involves measuring the time difference between the emission of a laser beam and reception of the reflected laser signal, in order to get the distance (range). The laser scanner system emits a laser beam at regular intervals. This beam is reflected by the Earth's surface and from objects on the Earth's surface. Depending on the reflectivity of the surface, parts of the emitted laser beam returns to the laser scanner system and stops a time counter which was started at the moment the laser beam was emitted. The distance can then be calculated taking into account the information of the position and attitude of the airplane by using GPS and INS (Inertial Navigation System) data (Figure 10). The premise is that radiation scattered from an object at a closer distance comes back sooner than that from an object at a longer distance. Typically the first and the last backscattered echoes are recorded. The first echoes can be used to assess the tree cover, while the last echoes can be used to model buildings. Laser scanning systems are active, consequently, day and night acquisitions are possible. Also shadows do not affect laser data.

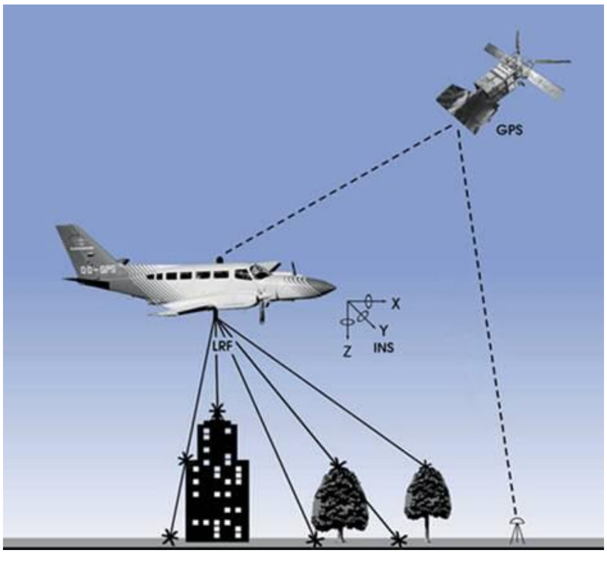


Figure 10. The principle of airborne laser scanning (adapted from www.eurosense.com)

The quality of products derived from laser scanning is influenced by a number of factors which can be grouped as follows: errors caused by the laser system (laser instrument, GPS and INS), and data characteristics (e.g. point density, first/last echo, flight height, scan angle), as well as errors created during processing of the data (interpolation errors, filtering errors, errors caused by improper break line detection, segmentation and smoothing of the data), and errors due to characteristics of the target (type of the terrain, flatness of the terrain, density of the vegetation canopy) (Ahokas et al., 2005).

A LiDAR product consists on a point cloud. Two initial raster products can be obtained from that data set: the Digital Terrain Model (DTM) and the Digital Surface Model (DSM). DTM is a bare earth model with all raised objects above the ground removed, while the DSM has the ground values included and raised objects above the ground (e.g. trees, buildings, cars, etc) (Figure 11). The DTM is generated by selecting terrain measurements (points) and interpolating them.

Figure 11. Difference between a Digital Terrain Model (DTM) and a Digital Surface Model (DSM)

Measurements for above-ground features have to be removed from the LiDAR data set before interpolation using ground filtering (elimination) algorithms (Meng et al., 2009a). These above-ground features will then integrate the DSM. Through the subtraction of the DSM to the DTM, a normalized DSM (nDSM) allowing the identification of the objects that lie above the terrain, is created (Figure 12).

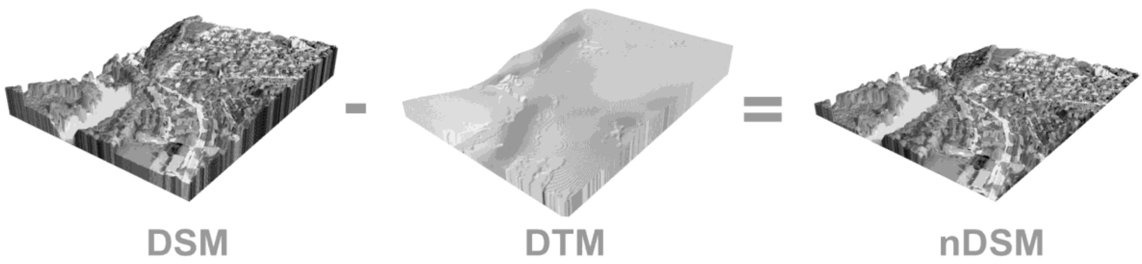


Figure 12. Creation of the normalized Digital Surface Model (nDSM) (adapted from Vozikis, 2004)

However, errors can appear in two situations: 1) when the DSM and the DTM are acquired in different dates, or 2) when the collection method differs (e.g., LiDAR flight or photogrammetric methods).

From elevation models, contour lines can be generated for topographic maps. Slope and aspect models can be created for integration into (land cover) thematic classification data sets or used as a stand-alone data layer. Furthermore, the model itself can be used to orthorectify remote sensing imagery and generate perspective views.

2.3.3 Auxiliary Data

Auxiliary data are data which enhance processing and utilization of the primary geographic data set selected for a mapping project. Auxiliary data include data collected by any platform or process. Examples for auxiliary data used in operational product generation are precipitation, temperature, elevation, soil type, human population density, census data or other spatial data that could provide an indication of the land cover class for a pixel/object like field data or higher-spatial resolution imagery. Expert opinion is still another source of auxiliary information.

After selecting the data set, the subsequent stage is to pre-process all data for further analysis.

2.4 IMAGERY PRE-PROCESSING

In the pre-processing stage the goal is to prepare the images for subsequent analysis, by correcting for sensor and platform specific radiometric and geometric distortions. Typically, this phase involves the geometric and radiometric transformations of the spectral data. Image pre-processing produces a corrected image, both geometrically and radiometrically as close as possible to the true radiant energy and spatial characteristics of the study area in the time of image acquisition (Jensen, 2005).

Besides the geometric and radiometric corrections, other operations such as image fusion, can also take place at this stage. The following sections present the most common approaches for image pre-processing.

2.4.1 Geometric Correction

These operations aim to assign a coordinate system to the image (geometric correction), to co-register images of different dates to ensure that, in multi-temporal studies, the same pixel is compared (image registration), and to correct geometric effects introduced by the terrain (orthorectification). The imagery geometric correction can then be achieved in two different ways: through an expedited geometric correction on planimetry using control points, or through a 3D orthorectification, much more accurate and that requires the Geometric Model of the Image Acquisition (MGAI).

Orthorectification

The orthorectification of a raster data set is then a pre-processing technique applied because satellite images do not show features in their correct locations due to displacements caused by the camera optics, viewing angles, and terrain relief. Orthorectification transforms the central projection of the image into an orthogonal view of the ground, thereby removing the distorting effects. The effect of other conditions during image acquisition, such as variation in viewing geometry and platform attitude, and Earth rotation, is also removed from the rectified image just as in standard image georeferencing.

For the correction it is necessary to know the terrain topography, usually modeled by a DTM. A DTM is a mathematical model that represents the terrain topography, based on spatial information (x, y, z) collected from sampled points on the ground, contour lines, photogrammetry or satellite imagery assets (e.g., radar images). However, the conventional orthorectification process does not take into account objects like buildings, bridges, trees etc. Such objects remain in perspective views in the resulting orthoimages and are distorted from their true positions (e.g., leaning buildings or bent bridges). Alternatively, DSMs can be used to orthorectify an image.

DSMs represent all elements at the Earth's surface (e.g., buildings, houses, trees) as well as natural terrain features. If a DSM is used to characterize the mentioned objects that caused the displacement, instead of the DTM, the displacements can be corrected and the results are called "True Orthoimages". However, this operation requires that at least an image from another viewing angle is available to insert the occluded information. Other common problems are "ghost images" that are created when the roofs of buildings are aligned with the footprint of the buildings, making the roofs appear twice. Zhou and Chen (2008) propose that really true orthorectification can only be achieved with a Digital Building Model along with a DTM. Figure 13 shows the deviation of the pixel in the image due to the effect of the relief, and the result of the orthorectification using a DTM and the sensor calibration values or orbital ephemeris data.

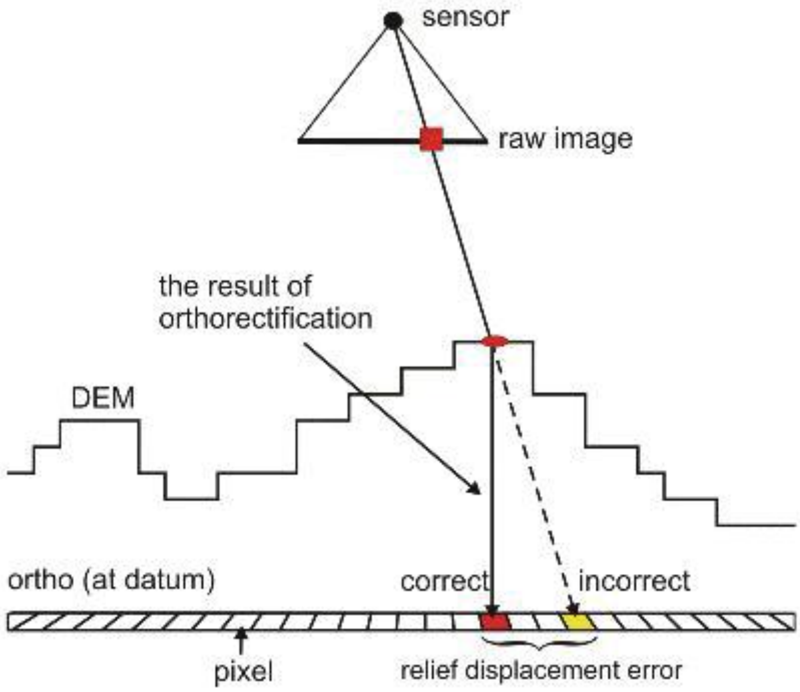


Figure 13. Orthorectification process using sensor geometry and a Digital Elevation Model (DEM) (adapted from PCI Geomatics, 2003).

To orthorectify an image, the software calculates a mathematical model that determines how an uncorrected image relates to real world locations on the Earth's surface. This can be achieved with different methods: 1) using GCPs with known 3D coordinates on the ground and 2D in the image, 2) using the sensor's rigorous model, or 3) using the rational function model:

- The simplest way to orthorectify an image is to use local observations of the surface, the GCPs. For each GCP, the values of the coordinates on the ground or in the reference data (x, y, and z) and in the image (line, column) are collected. Then, a polynomial function is adapted. To compute the unknown variables of a rational polynomial function using GCPs, a minimum of 7, 19, and 39 GCPs are required to resolve the first-, second- and third-order rational polynomial functions, respectively. This method does not take into consideration the physical reality and the characteristics of the image-acquisition geometry and is also sensitive to errors from GCP input and distribution. Consequently, in an operational environment, many more GCPs (at least twice as many) will be required to reduce error propagation (Toutin and Cheng, 2002);
- Alternatively, the process can be carried out using a sensor's model. The Satellite Orbital Math Model is a rigorous model developed by Thierry Toutin to compensate for distortions. This model includes physical parameters about the camera (e.g.,

focal length, pixel size, lens distortion), and orientation parameters like position and attitude of the sensor providing the physical imaging setting and transformations between the 3D object space and image space (Di et al., 2003). The computed math model calculates the position and orientation of the sensor at the time the image was taken. The accuracy of the Satellite Orbital Math Model is approximately one-third of a pixel for visible and infra-red satellite images, and approximately one pixel for radar images when quality ground control coordinates are used. However, the rigorous model is not always available (e.g., IKONOS) or when it is (e.g., QuickBird) is limited to some digital image processing packages (e.g., PCI Geomatics);

- The usage of the Rational Function Model (RFM) is another alternative for orthorectification, especially when there is no information on the sensor model (Tao and Hu, 2001). RFM is defined by 80 coefficients or less, called Rational Function Coefficients (RFCs). For QuickBird or IKONOS images, these RFCs are provided along with the imagery. Then, with the RFCs a simplified model of the sensor geometry (the RFM) can be created. With adequate control information, the RFM can achieve a very high fitting accuracy with sufficient speed to support real time implementations. This is the primary reason why the RFM has been used as a replacement sensor model (Tao and Hu, 2001). Unlike the previous alternative, there are several commercial software packages that already incorporate the RFM (e.g., ERDAS or ENVI). The RFCs relate the object point coordinates (x, y, and z) to image pixel coordinates (row, column) in the form of rational functions that are ratios of 3rd order polynomials. Numerous tests have shown that the use of RFCs allows an approximation to the rigorous model of the sensor without significant loss of quality (Tao et al., 2004). Although the collection of GCPs is not necessary, they can be used for further refine these models, allowing for better correlation between the pixels and their location in the field (Di et al., 2003). There are then two methods to improve the position of the coordinates obtained with the RFM. The first method is to compute new RFCs based on the ones provided by the vendor. Such high quality initial values of the RF make the solution of the new RFCs more stable and the computational process faster to converge. This method requires a large number of GCPs to compute the new RFCs. In fact, more than 39 GCPs are required for the third-order RF. The second method corrects the coordinates based on polynomial adjustments, whose parameters are obtained with GCPs. The first method is a direct method where new RFCs are calculated using the original RFCs. The second method is an indirect approach, since only the derived ground coordinates are refined and not the original RFCs. This last method is simpler to implement and requires less GCPs (Di et al., 2003).

The most common way to verify the quality of a georeferencing process is to calculate the Root Mean Square Error (RMSE) for a certain number of Control Points (CPs). These CPs should be well identified in the image and in the reference data and different from the GCPs already used in the correction process (See section 2.6). RMSE is a calculation of the average difference between the actual location of an element and the location shown on the corrected image.

Orthorectification accuracy is heavily dependent on the DTM accuracy. Also the satellite elevation angle and the off-nadir viewing angle affect its accuracy. The higher the elevation and the lower the off-nadir angle, the less distorted are the images and the better is the accuracy.

2.4.2 Radiometric Correction

The radiance measured by a sensor is a function of the surface characteristics, lighting, weather conditions, geometry of the vision, and measuring characteristics of the instruments (Jensen, 2005). Ideally, only the information that relates to the objects is of interest for land cover mapping. The need to correct the disruptive effects, however, is dictated by the specific problem under investigation (Lillesand and Kiefer, 2000). Before proceeding to the list of effects and their radiometric corrections, it should be noted that there are, in fact, errors due to bad weather in remote sensing data. The energy emitted from the Sun and captured by the sensor, if contaminated by the atmosphere, is still a valid signal, even when preventing the accurate measurement of the surface spectral reflection. However, many researchers consider that the atmospheric effects such as absorption and dispersion, affect the ability to extract useful information from remote sensing data, and as such should be eliminated (Jensen, 2005). Other authors argue that, given the inability to make a satisfactory atmospheric correction, the best option is not perform any correction at all (e.g., Caetano, 1995).

Radiometric correction (also referred to as image restoration) is used to modify DN values in order to account for noise, i.e., contributions to the DN that are not due to the feature being sensed but instead are caused by the intervening atmosphere, the Sun-sensor geometry or the sensor itself.

The atmospheric correction methods for remote sensing data can be grouped into absolute and relative. Absolute radiometric correction uses a model of the atmosphere and *in situ* atmospheric measurements taken at the time of image collection. The correction is done using the sensor's calibration coefficients and an algorithm generally based in radiative transfer code or, alternatively, using an empirical line calibration method. Thus the image is corrected for the atmospheric scattering and absorption. The general goal of this correction is to convert the digital brightness values recorded by the satellite sensor into scaled surface reflectance values (Du et al., 2002). The corrected values can then be compared or used with other scaled values obtained elsewhere.

On the other hand, relative radiometric correction techniques have been developed because the atmospheric data, necessary to model the atmosphere at the time of image capturing, are very difficult to obtain. The goal of a relative correction is then to normalize intensities in bands from a single-date image or from multi-date images. In a single-date data set, the bands' histograms are analyzed and the noise introduced by the atmospheric scattering is identified and subtracted in every band. Correcting multi-temporal data sets involves selecting a base image and then transforming the spectral characteristics of all other images to meet approximately the same radiometric scale of this base image. Generally, the normalization involves the selection of Pseudo-Invariant Features (PIF) that are foreseen to change very little over time (e.g., bare soil, deep water bodies or large rooftops). The image values are then subject to a regression to relate the PIF spectral characteristics from the base image, with the PIF spectral characteristics from other dates.

Besides the scattering and absorption effects caused by the atmosphere, the radiant flux can also be affected by the topographic characteristics of the imaged area, like slope and aspect. These conditions can contribute evenly to completely shade the areas of interest, thus affecting its brightness values. One common operation is the cosine correction. It is done by dividing all the pixels by the cosine of the zenith angle to make the illumination effects comparable. The Minnaert correction is an improvement on the previous method by introducing a constant that measures the extent to which a surface is Lambertian (i.e., a perfectly diffusing surface). Another radiometric data processing involves the conversion of the brightness values (DN) to absolute radiance values, using the senor calibration coefficients (the gain and the offset).

However, some authors suggest that when working in single-date applications over flat areas, and when the atmospheric effects are homogeneous across the area, is best not perform any type of correction (e.g., Hill and Sturm, 1991). Furthermore, in multi-temporal studies based on post-classification comparison for change detection, there is no need to atmospherically correct the individual image-dates (Singh, 1989). The general principle is that an atmospheric correction must only be applied if the training data set is to be used in other images besides the image under investigation (Jensen, 2005).

2.4.3 MULTIRESOLUTION FUSION

Image fusion is a method that combines images from different sources in order to complement and enhance its interpretation (Pohl and Genderen, 1998). Most EO satellites, such as SPOT, IRS, Landsat 7, IKONOS, QuickBird or OrbView, acquire one Panchromatic (Pan) band, with higher spatial resolution than the Multispectral (MS) bands. To explore the benefit of the enhanced spatial capability of the panchromatic camera and the enhanced spectral capability of the multispectral camera, fusion techniques were developed to merge both images. Pan-sharpened MS is a fusion product in which the MS bands are sharpened by the higher-resolution Pan image. Thus, applying spatial fusion algorithms, improves the geometric correction, promotes stereoscopic capabilities for stereo-photogrammetry, contrasts certain characteristics that are not visible on either single data alone, creates additional data to improve the classification, replaces missing information in an image with values of another image, or replaces defective data. This technique is particularly important for large-scale applications.

There are several techniques for imagery fusion. When the objective is to improve the visual quality of the images, the most common techniques are the Principal Component Substitution (PCS) and color space conversion between RGB (Red, Green, and Blue) and IHS (Intensity, Hue, Saturation) components (Zhang, 1999).

However, PCS and color conversion methods often distort, in part, the spectral characteristics of the original data (Chavez et al., 1991). To reduce the color distortion and improve the fusion quality, Zhang (2002) developed a new algorithm for imagery fusion that aims to reproduce the spectral characteristics of the original MS images and the spatial information available in the Pan image. This new algorithm is currently only implemented in PCI Geomatica software, in the module PANSHARP. It differs from the existing techniques in two ways: (1) it uses the least squares technique to find the best fit between the grey values of the image bands being fused and to adjust the contribution of individual bands to the fusion, reducing color distortion, and (2) employs a set of statistic approaches to estimate the grey value relationship between all the input bands to eliminate the problem of data set dependency (i.e. reduce the influence of data set variation) and to automate the fusion process (Zhang, 2004) (Figure 14).

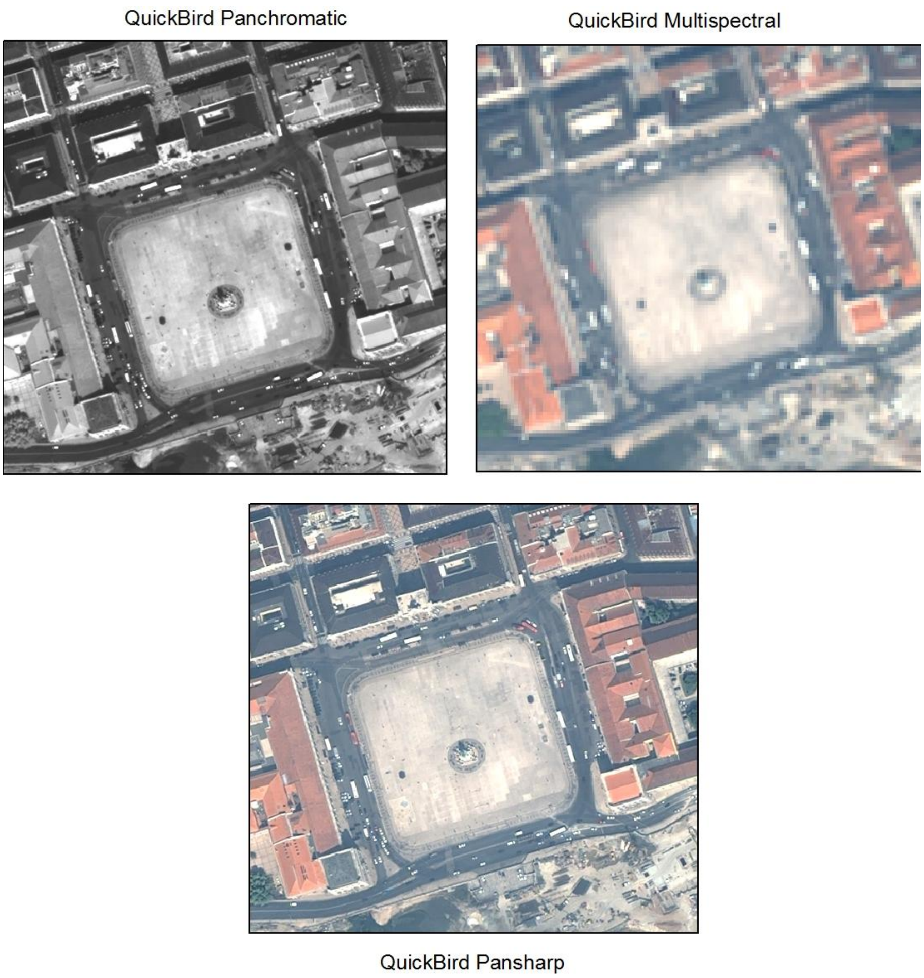


Figure 14. The original QuickBird panchromatic and multispectral images and the pan-sharpened image obtained with the fusion technique developed by Zhang (2002).

2.5 EXTRACTION OF THEMATIC INFORMATION

The extraction of categorical information on land surface can be accomplished in several ways. The following sections describe the two main methods for information collection from digital images: photo-interpretation and digital classification. The method’s choice shall take into account economic factors, time and available resources. Moreover, the selection of the proper data for thematic information extraction is crucial to the mapping quality. Indeed, the spatial resolution of images influences the accuracy and the detail of the mapped classes.

Huiping et al. (2003) examined the relationship between the quality of a classification, the scale of analysis and the image spatial resolution. Four spatial resolutions were considered (0.1, 0.2, 0.5 and 1 m) in a LULC map with 9 classes. The authors concluded that there is a relationship between the quality of the map produced and the image’s spatial resolution. However, this relationship is not equal for all classes: some improve with the increase of resolution and others not. For example, the classification of a port area has better results with higher resolutions (e.g., 0.10 m), but on the contrary, to classify large buildings, lower resolutions are desirable (e.g., 1 m). Chen et al. (2004), in a similar study, concluded that the more heterogeneous are the land cover units or the more fragmented is the landscape, the higher is the spatial resolution needed to obtain a good mapping quality.

2.5.1 IMAGE PHOTO-INTERPRETATION

The most common method to produce a LULC map is by visually analyzing aerial images. More recently, also high spatial resolution satellite images have been used for photo-interpretation, given the constant improvement of the more recent spaceborne digital sensors.

When one looks at an image, several objects of different sizes and shapes can be seen. Some of these objects are readily identifiable while others are not, depending on experience and individual perception of each observer. The image contains "raw" data, which when processed by photo-interpreters are transformed into usable information. The act of visually identifying what is in an image and transmitting that knowledge to others, is called imagery interpretation. The success of the interpretation of images varies with the interpreter’s training and experience, the nature of the objects, the analyzed phenomena and the quality of the images being used.

Although in general, all people have some experience of visually interpreting "conventional" photos, the interpretation of images differs from the everyday interpretation in four aspects: (1) elements are observed from directly above, (2) frequent use of wavelength outside the visible range, (3) visualization of the surface at different scales and unfamiliar resolutions, and (4) losing sense of depth when viewing a 2-dimensional image unless a stereoscope is used to simulate the third dimension of height (CCRS, 2009).

The systematic study of images involves, typically, some basic characteristics of the elements present in the image. The image analysis elements useful for a given task, and how they are treated, depend on the application. Recognizing targets is the key to interpretation and information extraction. Observing the differences between targets and their backgrounds involves comparing different targets based on any, or all, of the visual elements of **tone, size, shape, texture, pattern, height, shadow, site** and **association** (CCRS, 2009).

This 1st phase of visualizing objects in the image is called **photo-identification**. The following phase is to give a meaning to the object identified, which may be residential or industrial unit, working area or leisure, agricultural area or green space. This is the stage of **photo-interpretation** that, unlike the previous, requires a deductive analysis capacity by the interpreter. This analysis can take advantage of stereoscopic vision, expert knowledge and field work, since it is more a deductive stage than a visualization one. The knowledge of the image scale, the conditions of acquisition (local weather) and additional information such as date, time, film type or optical sensor used are necessary for the work of photo-interpretation.

The process of interpretation may be by direct or indirect recognition. The identification of a road can be made by direct observation. However, there are land covers that are recognized indirectly. The identification of a pipeline requires the observation of soil conditions while the identification of type of agricultural crop involves the use of agricultural calendars. In this context, the use of interpretation keys can facilitate the work of the photo-interpreter. An interpretation key can be defined as a set of guidelines used to assist interpreters in identifying features (see section 2.2.2). The success of an image interpretation depends strongly on the knowledge of interpreters and on how this knowledge is used in the process of interpretation. The development of an interpretation key is then a pre-requisite for a repeatable interpretation in all types of images. Basically, it helps the interpreter organizing the information present in image and also guides the correct identification of unknown objects. It serves also as reference material for new interpreters and allows working coordination in order to achieve homogeneous results.

Visual interpretation is a method widely used for production of thematic cartography, not only because it achieves good results, but also because an alternative method it is not always available. Examples of this type of applications are the CLC, COS'90 or CARTUS-AML cartographic products. However, visual interpretation has some drawbacks associated. On one hand, the number of distinguishable grey levels of the human eye (approximately 16) is considerably smaller than the range captured by digital sensors. Similarly, the human eye can only compare 3 bands simultaneously (in a RGB color composite). But the biggest disadvantage is that photo-interpretation is based on subjective assumptions. Green and Hartley (2000) found that the subjectivity in placing the boundary between elements which gradually tend to each other is the factor with greatest contribution to the positional error on a thematic map. This inconsistency may also create problems in map updating, even if made by the same person (Ahlcrona, 1995), causing the conclusions based on the analysis of these maps, to be unreliable. In addition to the intrinsic characteristics of human recognition, the entire cartographic framework based on photo-interpretation requires time and resource allocation.

Alternatively, there are automatic methods that are less subjective or time consuming, and require a minimum of resources, but having the disadvantage of being limited to computer algorithms and requiring a good knowledge of digital image processing. The following section describes the main methods for digital classification of satellite imagery.

2.5.2 DIGITAL IMAGE CLASSIFICATION

In opposition to the manual mapping by visual analysis, one can choose to classify the surface in a semi-automatic way. To do this, the images need to be available in digital format, in order to be analyzed by digital image processing software. Such software allows the manipulation and interpretation of digital images using a computer. Its purpose is to replace the visual analysis of images by a set of quantitative techniques that allow the automatic identification of objects. Generally, digital classification is the analysis of multispectral data and application of statistics that assign each pixel to a class. When these rules are based solely on spectral information existing in the image, the process is called *spectral patterns recognition.* Alternatively, when the decision rules are based on geometric characteristics such as shape, size or patterns, the process is called *spatial patterns recognition* (Lillesand and Kiefer, 2000). However, the aim is always to automatically classify the pixels of an image into LULC classes.

The spectral patterns recognition uses the spectral value recorded in each pixel as a basis for numerical classification. There are two techniques that make use of this information, but at different stages of the classification process: supervised and unsupervised classifications (see section 3.1, for more details on these techniques).

Techniques for spectral patterns recognition are already well established in the literature. However, recognition of spatial patterns is not a so "stabilized" scientific area and there is still much ongoing research. Many of these techniques attempt to systematize the human process of recognizing objects in an image. One possible strategy to model the spatial relationships and dependencies present in EO imagery is image segmentation. Classifiers that analyze features like the texture of the image or divide it into segments based on the neighborhood relations between pixels are discussed in greater detail in Chapter 3.

Although image classification is mostly performed automatically by the computer in the digital environment, human intervention, either prior to the classification or during post-classification, still plays an indispensable role in its success, even though this intervention is reduced markedly in comparison with manual interpretation (Gao, 2009).

Richards and Jia (2006), comparing two techniques for thematic extraction from remote sensing data – photo-interpretation and automatic classification – conclude that photo-interpretation, because it involves human interaction and high levels of decision, is a good technique for spatial evaluation but is poor in quantitative accuracy. The higher accuracy of computer analysis originates from its ability on processing every pixel in the image taking into account the full range of spectral, spatial and radiometric characteristics.

In Chapter 3 the most common digital classification methods for thematic extraction from VHR imagery will be discussed in detail.

After extracting thematic information, either by visual or semi-automatic methods, it is necessary to assess the quality of the map produced. The following section describes the last phase of a LULC mapping project.

2.6 ACCURACY ASSESSMENT

Accuracy can be defined as the degree of closeness between a measured value and its actual (true) value (or a value known to be true). Meanwhile, spatial data is a model of the real world, making it difficult to identify a true value. Instead, values which are accepted to be true are used to check data accuracy. All spatial data, being a representation of real world phenomena, are of limited accuracy. The important question is then how to measure accuracy and how to report it to the end users.

The International Standards Organization (ISO) is an international organization, founded by the United Nations, responsible for creating standards. ISO/TC 211 is the ISO's Technical Committee that develops standards for Geographic Information/Geomatics. The ISO 19100 series includes of approximately 35 items, and some are already completed and published. Among these are rules concerning the spatial data quality - ISO 19113:2002 (Principles of Quality) and ISO 19914:2003 (Quality Procedures for Evaluation). These documents establish the principles for evaluating and reporting the quality of geographic data. However, the standards do not attempt to define a minimum acceptable level of quality for geographic data. The quality of a data set is described using two components (ISO/TC 211, 2009):

- Data quality elements, together with data quality sub-elements and the descriptors of a data quality sub-element, describe how well a data set meets the criteria set forth in its product specification and provide quantitative quality information;
- Data quality overview elements provide general, non-quantitative information. These include elements on purpose, usage and lineage.

The following data quality elements (ISO 19113:2002), are used to describe how well a data set meets the criteria set forth in its product specification: completeness, logical consistency, positional accuracy, temporal accuracy, and thematic accuracy. Furthermore, a reference is made to the evaluation of the accuracy of extracted features, for single date analysis or change monitoring.

2.6.1 Completeness

Completeness refers to the presence and absence of features, their attributes and relationships. It is related with omission and commission errors. Errors of omission occur when items in the reference map are not represented in the produced map. The opposite situation corresponds to an error of commission. The correct comparison requires levels of generalization, accuracy and precision similar between Geographical Data Sets (GDS) (reference and produced). Then, once the positional error is defined, cases that exceed a given tolerance are considered errors of omission. However, this quantification is not trivial because in addition to counting errors, one should take into account the importance of the element under analysis (e.g., the absence of an airport may be more relevant than the absence of a building), or the extent of omission (e.g., a road completely or partially mapped).

The completeness of the model refers to the degree of agreement between the specifications of the database and the universe to be represented, and therefore is application-dependent. The completeness of the attributes relates to the degree of representation of all the needed attributes.

2.6.2 Logical Consistency

Refers to the degree of adherence to logical rules of data structure, attribution and relationships. It is a measure of internal validity and is calculated using information contained in the database. Data structure can be conceptual, logical or physical. Conceptual consistency analyses the adherence to conceptual schema rules. Domain consistency stands for the adherence of values to the value domains. Format consistency measures the degree to which data is stored in accordance with the physical structure of the data set. Topological consistency measures the correctness of the explicitly encoded topology (e.g., polygons that do not close, lack of connectivity between nodes of a network).

Those issues are beyond the scope of this thesis. They are tackled without needing to incorporate a comparison with reality: it may be performed completely automatically by comparing a given data model with the data.

2.6.3 POSITIONAL ACCURACY

The positional accuracy reflects the proximity between the position of an object in the database and in the reference data. It can be divided into absolute and relative accuracy. Absolute or external accuracy concerns the accuracy of data elements with respect to a coordinate scheme. Relative accuracy concerns the positioning of map features relative to one another.

These measurements are relatively easy to apply in point objects, but the same is not true when lines or polygons are considered. The assessment of positional accuracy of lines can be measured by the average distance between lines (measured in points or vertices, randomly distributed along the line) or by the Hausdorff distance (Matos, 2001). Another common approach for line and area accuracy estimation is using the concept of an error band surrounding the line of width epsilon, known as the Perkal epsilon band (Perkal, 1956).

In Portugal, the technical specifications for implementation of digital mapping at 1:1 000, 1:2 000, 1:5 000 and 1:10 000 scales, define values of accuracy for the planimetric numerical topographic model (IGP, 2005a). These values correspond to the RMSE. The RMSE is a frequently-used measure of the differences between values predicted by a model or an estimator and the values actually observed (equation 1 and 2). The RMSE is calculated by comparing the coordinates of sample points in the map with those in a source having higher accuracy.

$$RMSE_{MP} = \sqrt{\frac{\sum_{i=1}^{n}\left((M_{iT}-M_{iC})^2+(P_{iT}-P_{iC})^2\right)}{n-1}} \qquad [1]$$

where: n - number of points in the sample;

M_{iT}, P_{iT} - Accurate planimetric coordinates of point i

M_{iC}, P_{iC} - Planimetric coordinates of point i obtained in the cartography;

$$RMSE_{Z} = \sqrt{\frac{\sum_{i=1}^{n}(Z_{iT}-Z_{iC})^2}{n-1}} \qquad [2]$$

where: n - number of points in the sample;

ZiT - Accurate altimetric coordinates of point i

ZiC, - Altimetric coordinates of point i obtained in the cartography;

The IGP (2005b) establishes as planimetric accuracy for the 1:10 000 national mapping series that deviation should not exceed 1.50 m and that 90% of a sample should provide significant discrepancy equal or lower than 2.30 m. Regarding altimetry, the maximum value of the RMSE in *z* is 1.80 m and 90% of the sample must have an error lower than 3.00 m. These limits are lower than the 3-4 m, referred by Davis and Wang (2001), as being required by cartographic uses.

2.6.4 Temporal Accuracy

This measure of quality is divided into three parameters. The accuracy of a time measurement, that refers to the correctness of the temporal references of an item (reporting of error in time measurement). Temporal consistency, that deals with the correctness of ordered events or sequences, if reported. The last parameter is temporal validity, which concerns the validity of data with respect to time.

2.6.5 Thematic Accuracy

It is the accuracy of data attribute, defined as the proximity between attribute values and their true values. In the case of categorical attributes, the measure of accuracy relates to misclassification. The evaluation of the thematic accuracy is usually done by filling an error matrix. In order to properly generate an error matrix, one must consider the following factors (Congalton and Green, 2009): (1) ground truth data collection, (2) classification scheme, (3) sampling scheme, (4) spatial autocorrelation, and (5) sample size and sample unit.

So, after delineating the sampling scheme, the value of the units sampled in the reference map and in the produced map is retrieved, and the error matrix is then built up. The matrix's columns usually represent the reference data, while the rows indicate the classification generated from the remotely sensed data (i.e., the map). From this matrix it is possible to calculate a series of quality indices: global indices like the KHAT statistic (obtain in a Kappa analysis) and the Overall Accuracy, and individual class's indices like the Producer's and User's Accuracy. The Kappa analysis is a discrete multivariate technique. When applied to a single matrix, it determines if the agreement between the classification and the reference data is significantly greater than 0 (i.e., better than a random classification). The Kappa analysis can also be used in accuracy assessment to statistically determine if one error matrix is significantly different from another. Overall accuracy is simply the sum of the correctly classified sample units divided by the total number of sample units in the error matrix. Producer's and User's accuracies are ways of representing individual class accuracies instead of just the overall classification accuracy (Congalton and Green, 2009).

No consensus has been reached on which measures are appropriate for a given objective of accuracy assessment, although the Kappa statistic seems to be generally favored (Stehman, 1997). Fitzgerald and Lees (1994) proposed "that the Kappa test statistic be used in preference to the overall accuracy as a means of testing classification accuracy based on error matrices." Fung and LeDrew (1988) concluded that "accuracy indices based on the producer's accuracy and overall accuracy may tend to be biased towards the category with a larger number of samples," and recommended that Kappa be used because "all cells of the error matrix are considered." Liu et al. (2007) made a comparative assessment of the measures of thematic classification accuracy. The authors recommend that user's accuracy and producer's accuracy and the overall accuracy should be provided as primary accuracy measures. Two relative entropy change measures (relative change of entropy given a category on map, and relative change of entropy given a category on ground truthing) and the normalized mutual information using the arithmetic mean of the entropies on map and on ground truthing, can also be provided as supplementary measures. Stehman (1997) concludes that selecting an appropriate accuracy measure depends on the objectives of the assessment, which are in turn determined by the objectives of the mapping project. If the objective is to describe the accuracy of a final map product, the overall proportion correct, user's accuracy, and producer's accuracy have a direct probabilistic interpretation in terms of the actual population represented by that map. When the assessment objectives are to compare error matrices, then the choice of an appropriate parameter becomes less clear. If a single summary measure of the error matrix is employed, any of the parameters, overall proportion correct, Kappa test, Conditional Kappa or Tau are potentially applicable, but none of these parameters directly takes into account specific objectives of a mapping project.

These metrics are commonly used in pixel-based maps, where the evaluation is easily done by comparing the labels of homologous pixels of the raster images. However, the method only considers the thematic or class accuracy of a given point/pixel/window. When evaluating an object-based classification, it is also required a measure or assessment of the geometric accuracy of the objects/polygons that have been created and classified (Schöpfer and Lang, 2006). This implies assessing properties like shape, symmetry and location.

2.6.6 Object-Based Accuracy Assessment

Pixel-based performance metrics give estimates of the area correctly classified. However, in an object-based evaluation, the goal of object detection is usually a distinction between two classes, object and background. In this situation, Song and Haithcoat (2005), suggest three levels of quality evaluation that can be preformed, depending on the application requirements: number-based indices, area-based indices and RMSE and, shape similarity indices.

Number-based indices

These are simple measures that allow a quick assessment, and can be used when no geometric accuracy or shape analysis are required. Number-based indices account for completeness (also refereed as detection rate) and correctness. The completeness is the ratio, expressed as percentage, of correctly identified objects to the total number of reference objects of the same class. The correctness is the percentage of correctly identified objects to the total number of identified objects of the same class. The completeness stands for the Producer's Accuracy and the correctness stands for the User's accuracy. Both indices are considered to be optimistic since an object is usually considered to be correctly extracted even if only a small part of it overlaps a reference object (Song and Haithcoat, 2005).

To assess the completeness and correctness, simple counting measures can be applied. One possible way is to determine, for each classified object and for each object in the reference, a central point (centroid). For each object in the reference, the number of central points of detected objects that fall inside the reference object is counted, and considered for completeness analysis. In a similar way, for each classified object, the number of reference centroids inside the classified object is counted, and is used for correctness analysis. (e.g., Rutzinger et al., 2009, Santos et al., 2009).

Area-based indices

Considering the area rather than the simple overlap/ no-overlap of objects, more reliable evaluation of the quality of extraction can be drawn. Comparing the results of the automated extraction to reference data, four categories are possible for each object. If the extracted object corresponds to an object in the reference, than it is classified as a

True Positive. A False Negative is an entity corresponding to an object in the reference that was missed in the classification, and a False Positive is an entity classified as an object that does not correspond to an object in the reference. A True Negative is an entity belonging to the background both in the classification and in the reference data (Shufelt, 1999). Still, another possible mistake can occur besides the already mentioned ones: one classified object can overlap two (or more) objects in the reference map. This situations in noted as crosslap (Shan and Lee, 2005). This situation can easily occur when extracting buildings in densely built-up areas (e.g., Shan and Lee, 2005; Santos et al., 2009).

Shape similarity indices

Large-scale maps, like cadastral applications, require further information concerning the shape of the extracted objects. The existing shape descriptor methods can be classified into boundary-based and region-based approaches (Zhang and Lu, 2004). Boundary-based representation describes the closed curve surrounding the shape and can be specified by boundary moments, turning functions, polygonal and curve decomposition, compactness or Fourier descriptors, among others (Zhang and Lu, 2004). The region-based approaches, on the other hand, consider the object as a whole, and its characteristics are described by the geometric primitives like area or orientation and can be assessed though area or perimeter differences or, if applied, corner differences (e.g., Santos et al., 2009). These indices are easy to calculate and can be expressed as percentage of absolute area (or perimeter, or corner) difference between extracted and reference objects.

2.6.7 Change Detection Evaluation

A key issue in any change detection accuracy assessment is the realization that change is a rare event and sampling must occur to specifically deal with this issue. Also problems in collecting reliable temporal field-based data sets arise in a multi-temporal study. Furthermore, positional errors are also critical. Therefore, much previous research on change detection cannot provide quantitative analysis of the research results (Lu et al., 2004).

Although standard accuracy assessment techniques were mainly developed for single-date remotely sensed data, the error matrix-based accuracy assessment method is still valuable for evaluation of change detection results. The change detection error matrix has the same characteristics of the single-date classification error matrix, but also assesses errors in changes between two time periods and not simply a single classification. It is important to note that the change detection error matrix can also be simplified or collapsed into a 2×2 no change/change error matrix. From this no change/change error matrix, the analysts can easily determine if a low accuracy was due to a poor change detection technique, misclassification, or both (Congalton and Green, 2009).

3. FROM EARTH OBSERVATION DATA TO THEMATIC INFORMATION: LAND USE AND LAND COVER MAPPING APPROACHES

EO images, available in digital format, are structured in regular arrays of image elements, called pixels, which correspond to an area of the Earth's surface. Each pixel represents the amount of energy reflected by the objects on the surface in different ranges of the electromagnetic spectrum. The goal of any methodology for image classification is the allocation of a thematic class to all pixels of the image, thus automating the process of visual interpretation.

Over the last decades of remote sensing research related to LULC classification, several improvements have been made, with high impact on the exploration of EO data. This chapter presents the evolution of image classification approaches used in land cover mapping.

There are several approaches to convert the data existing in an image into thematic information. One method is to manually collect the information through visual analysis. Alternatively, there are several algorithms developed for imagery classification, available in commercial software packages. One of the most common methods is the multispectral classification. This assumes that the image of a given geographical area is collected in multiple regions of the electromagnetic spectrum. The conventional approaches are based on information available at the pixel level (supervised and unsupervised classifiers) and were developed to classify images of medium resolution (e.g., Landsat-MSS and TM). The thematic information is obtained through the calculation of multivariate statistics on the available spectral information of each pixel. Consequently, this type of approach is not comparable with the photo-interpretation produced by the human brain (Blaschke, 2004).

When it comes to the study of urban/suburban LULC, spectrally-based techniques have some drawbacks (Zhang et al., 2002). Urban areas are heterogeneous in nature. They may include different land cover types, such as concrete, asphalt, trees, grass, water, soil and all kinds of roof materials, which have different radiometric characteristics in a remote sensing image. It is then impossible to define a spectral homogeneous class such as 'Urban'.

To improve the classification's quality, new approaches such as merging data from various sources (multi-source data fusion) and models for contextual classification (Binaghi et al., 1997; Solaiman et al., 1999; Solberg, 1999; Melgani and Serpico, 2002) were tested. However, in the classification process, the photo-interpreter, implicitly, also uses structural knowledge: it is not only the context but also the information about the shape and spatial relationships between regions of the image (Blaschke, 2004). Thus, with the provision of VHR images, the spatial component is now available digitally. The spectral information is no longer the only dimension used in classification, making it important to introduce new components in the classification, that until now were considered irrelevant: the information of shape and spatial arrangement of the elements of an image. Thus, new methods that follow an approach based on the object emerged as an alternative to the traditional pixel-based methods. Although the object-oriented approach was already mentioned in the literature a few decades ago (e.g., Kettig and Landgrebe, 1976; Haralick and Shapiro, 1985), only the latest technological developments with regard to hardware, software and availability of images of high resolution, allowed operationalize this concept (Blaschke et al., 2004).

3.1 DIGITAL CLASSIFICATION AT THE PIXEL LEVEL

The traditional mapping approaches based on EO data use the spectral information available at the pixel, to classify the whole image. How this classification occurs depends on whether a supervised or an unsupervised approach is chosen.

In **supervised classification**, the classifier assigns a class to each pixel based on statistical information from a number of samples/training areas previously selected by the analyst. Thus, the supervised method relies on *a priori* decision on the information classes present in the map area. In **unsupervised classification**, on the other hand, the classifier, through the analysis of the whole image, groups the pixels into spectral classes which are then assigned to thematic categories by the analyst. In unsupervised approaches, the information classes are then decided *a posteriori*. The main difference between the two methods is that supervised classification assumes that some locations of the thematic classes are known, and then uses statistical parameters characteristic of these samples to estimate all other locations. In unsupervised classification, in turn, there is no knowledge of the area. The 'natural' data groups (clusters) are identified using assumptions inherent to the selected methods. Both approaches typically use hard classification logic to produce a map with discrete categories (Jensen, 2005).

The classification methods can be further divided into **parametric** and **non-parametric**, if it is assumed that the data follows a normal distribution or not. Typical parametric supervised classifiers include the Maximum Likelihood, Minimum Distance or Mahalanobis Distance. Non-parametric supervised classifiers include methods such as the Parallelepiped, Neural Networks, Decision Trees, or Support Vector Machines. The parametric unsupervised classifiers more common are the ISODATA (Iterative Self-Organizing Data Analysis Technique) and K-Means algorithms. Less conventional methods include, for example, post-processing adjustment (Lark, 1995) or the progressive generalization (Cihlar et al., 1998).

Unsupervised classifiers generate clusters of spectral signatures by setting parameters like: 1) measures of similarity between signatures, 2) distances between clusters centers, and 3) criteria for merging clusters. The technique's premise is that the values that correspond to the same class shall be closer in the multispectral space, while data from different classes must be well separated. The spectral clusters are then interpreted by the analyst that attributes the information class. The two most frequently clustering algorithms used are the **K-Means** and the **ISODATA**. Both algorithms are iterative procedures.

Neural Networks, through the implementation of pattern recognition and sophisticated learning algorithms, allow building predictive models from large databases. It consists of a number of nodes (in analogy with the neurons of the human brain), and potentially unlimited intermediate layers containing intermediate nodes and links (in analogy with the human dendrites and synapses). Weights are assigned by a squashing function that calculates the output of a node as a weighed sum of the entries. A Neural Network model is created by providing it with many examples (input variables and output from training records). It is then a computer architecture that achieves its performance from massive parallelism and a dense interconnection of simple computational elements. Comparing the training results with the ones obtained by the Neuronal Network, one can make small changes on the Neuronal Network by changing the weights of the connections, i.e., the network "learns". Although based on the model of the human brain, it is no more than a mathematical function that calculates an output based on a set of input values. However, there is no descriptive element on the network model, so it is a technique often called "black box technology."

Decision Trees, such as neural networks, are learning algorithms. Each node in the tree represents a question, and the branches represent the possible answers. Decision Trees-based classifiers find ways to divide the universe into several successive subsets until each one covers only a class or until a class shows a clear majority, not justifying further divisions. The resulting trees are reasonably comprehensible and can be easily used to obtain a better understanding of the phenomenon in question. Figure 15 presents the conceptual model followed in a digital classification of satellite imagery, at the pixel level.

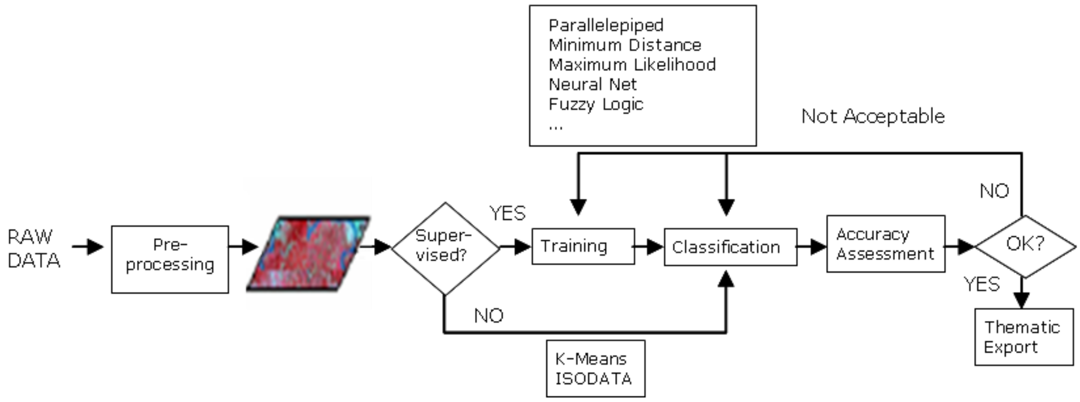


Figure 15. Traditional digital classification approach at the pixel level (adapted from Mo et al., 2007)

Lizarazo (2006) compared the performance of a Neural Network with a Decision Tree and a Maximum Likelihood algorithm, to classify LULC in QuickBird images. All algorithms operated on the multispectral bands and on a textural band (with the classes' borders). For the land cover classification, the best method was the Maximum Likelihood classifier with an Overall Accuracy of 82%, followed by Neural Network with 79%, and the Decision Tree, with 72%. For the land use classification, landscape metrics were tested along with the classifiers. The best classifier was the Neural Network with an Overall Accuracy of 84%, followed by the Decision Tree with 69% and Maximum Likelihood with only 42%.

All of the classification methods at the pixel level have advantages and disadvantages, and no method can be considered best for all applications. The main disadvantage of the pixel approach is that each pixel is classified individually, without taking into account the information contained in neighboring pixels or the fact that certain thematic classes are not internally homogeneous (e.g., single-family housing). The classification is solely based on statistical processing of spectral values recorded in each pixel. These problems have been known for some time (Markham and Townshend, 1981; Woodcock and Strahler, 1987).

The correct classification of images is very difficult in an urban environment based solely on spectral information since such areas are characterized by the presence of spectrally heterogeneous classes (Martin et al., 1988; Hoster, 2007). Furthermore, Foody (1999) identifies some problems for the Maximum Likelihood classifier, one of the most used: (1) being a parametric classifier, the data are assumed to have a normal distribution, which often does not happen; (2) requires a large number of training areas, (3) does not allow the direct use of ancillary information in the process of classification, (4) is very demanding in computational terms, being relatively slow (a problem that can be significant when dealing with the large volume of data from very high resolution remote sensors).

The success of a classification in urban areas requires thus the application of alternative approaches to the traditional methods here exposed to extract information. The following sections describe more sophisticated methods that operate based on the pixel values and on other characteristics present in the image.

3.2 DIGITAL CLASSIFICATION WITH CONTEXTUAL INFORMATION

When mapping urban areas, the specificity of such environment must be taken under consideration: in an urban space co-exist a variety of objects with different spectral signatures, which often are not recognizable at the pixel level. The classifiers that operate on a pixel basis are not adapted to deal with this complexity. An alternative is the application of contextual classifiers.

Texture and structure analyses are among the approaches used to incorporate spatial information into the classification. Texture may be understood as the spatial variation in levels of grey in an image. Several methods have been developed to describe and classify the texture. The higher the variability, the less homogeneous or uniform the image texture will be: regular textures generally correspond to built-up areas, whereas irregular textures are typical of natural environments.

When a pixel window of a given size (e.g., 3x3) is moved all over an image, a frequency table can be generated for each class in the image, except for those pixels close to the image boundary. Because the information in a pixel window is used to classify a single pixel – the central pixel – this type of classification is called a contextual classification. The different types of spatial relationships usually observed between elements/areas of an image are the distance, direction, connectivity and inclusion. Therefore, the analysis quantifies the differences in grey levels (contrast) within a predefined area, with or without an established direction. The choice of window size is critical to the success of the operation. If the window size is too small, sufficient spatial information cannot be extracted to a frequency table to characterize a land-use type. If the window size is too large, much spatial information from other land-use types could be included.

Common textural classifications include approaches based on simple statistical transformations (e.g., average of neighboring pixels), in spatial co-occurrence matrix (e.g., Gray-Level Co-occurrence Matrix - GLCM), the texture spectrum (based on the comparison - higher, lower, or equal - of the grey levels of a central pixel and its eight neighbors), and measures of fractal dimension. All of the above textural methods are more or less dependent on some type of parameters (e.g., the displacement vector, the size of the window, the statistics used, the threshold, the number of grey levels used), that are related to the spatial and spectral resolution of the image and the spatial characteristics (e.g., dimension, shape) of the themes to be detected (Pesaresi 2000). However, when reviewing the literature, in most cases, the parameters are decided by trial-and-error experimenting, by subjective thinking, or not explained at all. This makes these textural measures unreliable and difficult to compare with each other. Texture measures derived for solving one geographical problem may not be useful for other applications.

The GLCM algorithm has now become the most well-known and widely-used method to describe texture features (Xu and Gondra, 2010), since it was proposed by Haralick in the 1970s (Haralick et al., 1973). The GLCM approach is a statistical method for capturing the spatial structure of an image in a given band pass by statistically sampling the way that certain grey-levels occur in relation to other grey-levels. The GLCM analysis produces texture measures that can be grouped according to the purpose of the weights in each measure. The groups include measures of contrast, measures of orderliness, and descriptive statistics. Representative measures include the mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment and correlation.

During the classification stage, the texture images can be used alone or in combination with the original bands. The combination permits to introduce in the classification process spatial information of objects of different classes, thus improving the final results (Wikantika et al., 2000; Pesaresi, 2000, Zang et al., 2003).

Philpot and Chavarria (1994) compared two classifiers based on spectral and textural information in a Landsat TM image. The first was based on a Maximum Likelihood classifier with a texture band added to the set of spectral bands. This additional band was based on an edge-preserving smoothing filter. The second classifier was a spectral-texture pattern matching that recognizes texture patterns based on spectral and spatial similarity. This algorithm uses the spectral and spatial characteristics of training data to form textural primitives. The results of the textural classification were compared with a purely spectral classification performed with the Maximum Likelihood classifier. In a quality analysis, the authors found that the introduction of the textural band in the spectral classification had no effect on the quality of the produced maps. Only the spectral texture pattern matching approach yielded different (and improved) classification accuracy. The authors conclude that texture can only be useful in the context of a neighborhood of pixels. Although the edge-preserving segmentation procedure defines the pixel texture in terms of a neighborhood, each pixel is then treated as if it had a texture independent of its neighbors. The pattern matching, on the other hand, characterizes a class in terms of both spectral and spatial patterns simultaneously.

Contextual algorithms were also used by Jaakkola (1994), Fuller and Brown (1996) and Olsson et al. (1997) to obtain the generalization of CLC maps from national LULC maps with higher detail than the defined as the standard for the CLC.

Caetano et al. (1997) developed a series of algorithms, for editing raster files obtained from a pixel-based classification. Contextual classifiers were developed for classes that could not be identified at the pixel level (e.g., airport, stadiums and associated sport fields, beaches and dunes). The methodology was tested using two images, SPOT-XS and SPOT-Pan, of Lisbon and surroundings. Examples of developed algorithms include the discrimination of three types of residential areas based on the abundance and spatial arrangement of vegetation. In the final map, 19 LULC classes were identified with a Kappa value of 86%.

Karathanassi et al. (2000) presented a method that classified built-up areas according to their density into three categories, using a SPOT-Pan image of the city of Athens, Greece. For the classification, three texture algorithms, a frequency-based algorithm and two co-occurrence matrix-based algorithms, were developed, tested and evaluated for different pixel windows in order to identify and classify urban areas according to their density (high, medium and sparse). A supervised classification with the Maximum Likelihood classifier was also carried out, for comparative purposes. The developed algorithms were equally effective when windows larger than 31x31 pixels were used. For such windows, the Overall Accuracy of the method ranged from 83 to 90%, whereas the Maximum Likelihood classifier obtained 80%. Significant improvements (up to 0.16 units for the Kappa value, and about 50–60% for the accuracy of each of the building density classes) were achieved when compared to the Maximum Likelihood classifier. All of the three algorithms proved to be efficient, with slightly different performances.

Zhang et al. (2003) studied urban spatial patterns using textural analysis on a SPOT-Pan image of Beijing, China. Supervised classifications were applied using various spatial and structural features produced from the image. Textural features, including eight from the GLCM method; a computationally efficient texture feature, the Number of Different Grey-levels (NDG); and a structural texture feature, Edge Density (ED), were evaluated. The authors found that single texture features performed poorly. The values of quality increased with increasing number of textural features (up to 3 or 4). The greater the number of features combined the smaller difference between the combinations. The results showed that a smaller number of textural features are needed for homogeneous areas. Features NDG and ED combined with the GLCM produced results similar to the GLCM features alone. The best un-stratified classification in this study produced an Overall Accuracy of 72% for the whole study area, with a Kappa value of 67%. This is a significant improvement over the accuracy of original SPOT-Pan image alone (27%). The best stratified classification, which resulted from the combination of the best classifications from the three stratified regions, was able to achieve an Overall Accuracy of 79% and a Kappa value of 75%, which is about two times better than the result from original SPOT-Pan image. This method has clearly shown the spatial pattern of the city.

3.3 CLASSIFICATION AT THE SUB-PIXEL LEVEL

Because the urban environment includes a complex mix of natural and man-made urban features often interwoven with one another, there is a need to deal with a complex mixture of spectral responses (Forster, 1985). The concept of mixed pixel reflects the fact that, in a single pixel, several land cover classes are represented, making its spectral signature not entirely 'pure' (Campbel, 1996) (Figure 16).

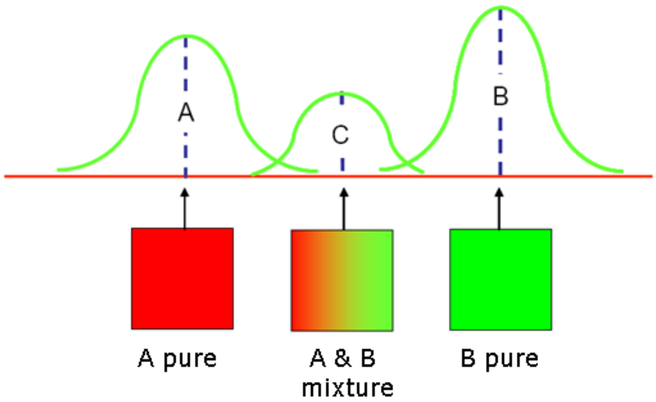


Figure 16. Spectral confusion caused by the mixture land use of classes (adapted from Tenedório et al., 2006)

A solution for this problem is the decomposition of the spectral values present in the pixel. One method is the Spectral Mixture Analysis (SMA) that assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel, called endmembers (e.g., asphalt, concrete and brick) (Lu and Weng, 2004; Small, 2001). In fact, SMA is a technique used to measure the percentage of spectra for each land-cover type in a single pixel. With a known number of endmembers and known spectra of each pure component, the observed pixel value in any spectral band is modeled by a linear combination of the spectral response of a component within the pixel. Another output of the model is the image of the mean square error. In this image, an error is estimated for each pixel when modeling the signal received by satellite through the linear combination of the pure components used in the model.

To decompose the existing information at the pixel level, one of the most used models is the Vegetation, Impervious surface, and Soil - VIS (Ridd, 1995). According to this model, the land cover in urban environments is a linear combination of three elements: Vegetation, Impervious surface, and Soil (Figure 17). More recently, Lu and Weng (2004) tested a new combination (vegetation, surface sealed and shadow), more adapted the urban environment.

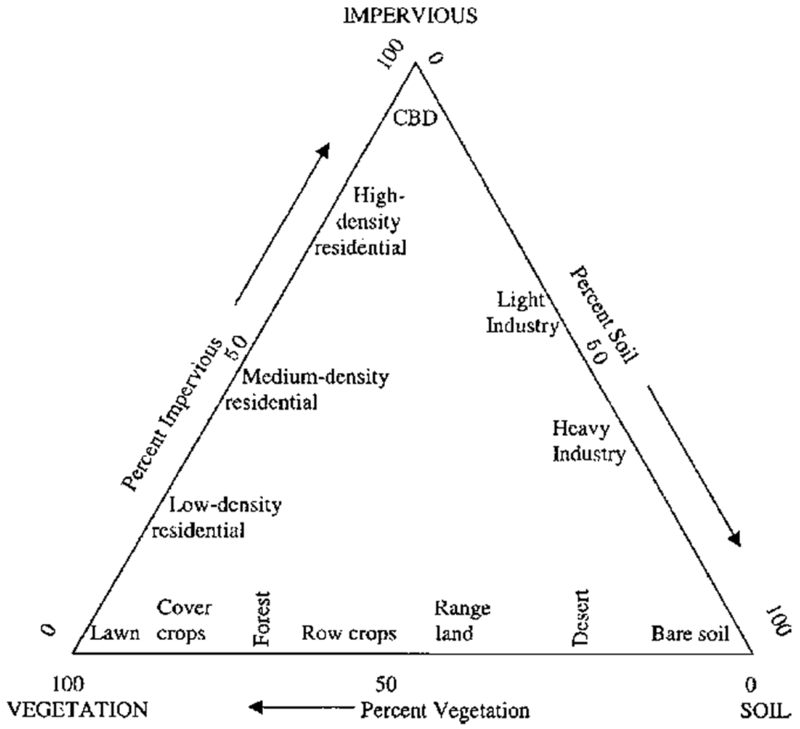


Figure 17. Elements of urban landscape described by the VIS model (Ridd, 1995)

Tenedório et al. (2006) studied, for the Lisbon Metropolitan Area, the application of a sub-pixel technique called Linear Spectral Unmixing to characterize the land use. The model applied to decompose the pixel values was the VIS model. The study utilized two Landsat TM (1987 and 1997), a Landsat ETM + (2000) and a SPOT 5 image (2004), and 19 LULC classes were mapped. The authors concluded that the methodology clearly identified the classes, and was valid to characterize the structure of LULC at the municipal level. However, no values of accuracy for the thematic maps were presented.

Nichol and Wong (2007) evaluated the effectiveness of SMA on medium and VHR images, to identify areas of grass and trees in urban environments. It was demonstrated that, unlike in medium-resolution images, in the IKONOS images, the grass and trees each constitute distinct endmembers. This occurs because the shadows in the urban environments, when using high spatial resolution data, can be identified at the pixel level, avoiding mixing of components.

3.4 FUZZY CLASSIFIERS

Most classification algorithms that have been used in operational programs are "hard" classifiers in the sense that the output of classification is one and only one class for each pixel. Such rigid spatial models consisting of discrete, sharply defined, homogeneous classes, ignore the geographic variability and complexity within nature and the error inherent in the measurement of it (Burrough 1989). Thus, a considerable amount of information is lost when sharp edged entities are combined. Fuzzy set theory provides more appropriate classifiers for LULC classes that have soft transitions rather than hard boundaries. The fuzzy theory was firstly proposed by Zadeh (1965). Unlike traditional set theory, where set memberships are crisp and binary, fuzzy set theory permits partial membership. The degree of membership is represented by a fuzzy membership value that ranges between 0 and 1, whereas the extremes 0 and 1 are the only available membership values in traditional set theory (Jensen, 2005; Atkinson, 1999) (Figure 18). Therefore, fuzzy classification offers a better alternative for urban land-use mapping, because it can indicate the primary, secondary, etc., land-use simultaneously. Soft classification has been proposed in the literature as an alternative to hard classification due to its ability to deal with mixed pixels.

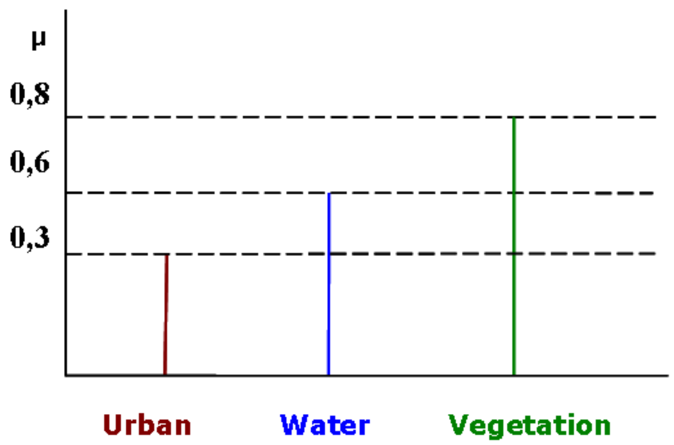


Figure 18. Fuzzy classification for classes "Urban", "Water" and "Vegetation". The image object is a member of all classes, with different degrees of membership (adapted from Baatz et al., 2004)

The fuzzy sets are characterized by membership functions, with the value of membership varying within any range of values but usually, by convention and simplicity, limited to the continuous interval [0,1] with a gradual transition from a total membership at 1 to no membership at 0 (Power et al., 2001). The result of fuzzy classification is therefore a set of images with the degree of membership of pixels to the classes defined. The highest degree of belonging to a class determines the final classification (Figure 19). Most frequently-used algorithms include fuzzy c-means clustering (Bezdek et al., 1984), supervised fuzzy classification (Wang, 1990) and possibilistic c-means clustering (Krishnapuram and Keller 1996).

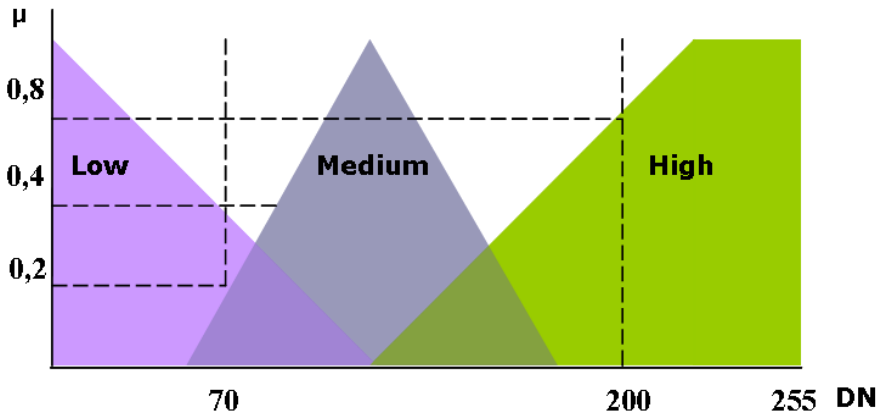


Figure 19. The membership functions of the element (μ) define the fuzzy set low, medium and high for this element (adapted from Baatz et al., 2004)

Siachalou (2004) tested a supervised classification with the Maximum Likelihood algorithm in an IKONOS pan-sharpened image. The result was not satisfactory because some streets were mixed up with buildings, and areas of bare soil were misclassified as burnt forest. So an approach based on a fuzzy classifier was tested. The image was stratified into two areas: an urban zone and a hilly tree-covered zone. After selecting samples for each image part, a supervised fuzzy algorithm was applied. The method generated three files: a file with the distance values of each class mean, and two images with the result of the fuzzy classification. One image contains the best result of classification, while the other contains the second best result. Then, through a Fuzzy Convolution operator, a single image was created by calculating the total weighted inverse distance of all the classes in a 3×3 window of pixels. Then, the class with the largest total weighted inverse distance over both fuzzy classification layers was assigned to the central pixel. The urban stratum obtained an Overall Accuracy of 84% and a Kappa value of 78%.

3.5 USE OF ANCILLARY DATA IN THE CLASSIFICATION PROCESS

Most approaches for extracting thematic information at the pixel-level are based only on spectral data to differentiate the classes. When mapping urban environments at large scale, relying solely on the spectral information may limit the accuracy of the classification due to the high heterogeneity typical of urban areas. The accuracy can be improved with the integration of additional data and/or information other than the imagery (Strahler et al., 1978, Hinton, 1997, Franklin et al., 2000). Such data and information, also known as "**ancillary data**" in the literature, are often composed of map-based thematic data, terrain data and non-spatial data. Terrain data can be derived from digital terrain models: elevation, slope, and exposure are used in the classification stage (e.g., Hofmann, 2001a; Gerçek, 2004). The inclusion of other data, such as environmental factors affecting the distribution of vegetation, like wind and insolation (e.g., Frank, 1988) or census data (Mesev, 1998; Martinuzzi et al., 2007, Rocha e Sousa, 2007) is also common.

There are three main ways to combine data with satellite images, according to their use before, during, or after classification (Hutchinson, 1982):

- Pre-classification stratification - the study area is stratified based on auxiliary information, and classification of the image is made separately for each stratum (e.g., Caetano et al., 1997). Thus, it is possible to reduce the study area under analysis, thereby decreasing the internal variability of each class, improving the chances of success and reducing the processing time;
- Integration of ancillary information in the classification algorithm - the information is used as an auxiliary channel (band) in the additional classification (e.g., Strahler et al., 1978; Santos et al., 2010b). Another approach is the inclusion of a band with *a priori* probabilities of a pixel belonging to a particular class;
- Improving post-rating - the information is used to help resolve any ambiguities after the classification (e.g., Hutchison, 1982).

Caetano et al. (1996) mapped Lisbon and surroundings, with spectral data (SPOT images) and ancillary data (road network and census data). The ancillary data were integrated sequentially, in order to evaluate the improvement on the accuracy of land use maps achieved by the integration of each type of data. Initially, a map based on satellite images, using the pixel-level classifiers and contextual classifiers was produced. Then, in a second stage, the road network was integrated with the spectral data in order to produce a new map. In the third phase the final map is produced with the census data. The analysis of quality of the three maps produced showed that the successive introduction of auxiliary information provided a better classification of land use, with the Kappa value increasing from 78% in the first map to 85% in the second phase and 88% in the last stage.

Navarro (1999), in addition to the work of Caetano et al. (1996), produced a land use map for the Great Area of Lisbon, at 1:50 000 scale, from SPOT and Landsat images and using the CLUSTERS' nomenclature. The integration of ancillary data, including information on roads and the information collected in municipalities, was used to (1) map classes that could not be identified based on spectral data, and (2) improve the discrimination of other classes. The proposed methodology produced land use maps with 26 classes, with an Overall Accuracy greater than 80%. The author concluded that the satellite data alone were not sufficient to generate maps of land use with the specifications and qualities required by Eurostat, instead the integration of auxiliary data being necessary. In this study, accuracy above 80% was achieved for most classes, incorporating only data on the road network and the information collected in municipalities, in particular, the information extracted from the PDM. Another important conclusion was the need to use algorithms that analyze the spatial arrangement of pixels, for a comprehensive use of satellite data when producing land use maps based on very detailed nomenclatures, such as the CLUSTERS nomenclature.

Rocha (2005) presents a methodology for image classification with integration of auxiliary information. The methodological steps included stratification pre-classification, application of the Bayes classifier and Maximum Likelihood, and post-classification. The study area was located in the municipality of Oeiras, Portugal. The spectral data consisted of a Landsat ETM+ image. The selected ancillary data were the census, the PDM and the road network. The census data were used to define the *a priori* probabilities of occurrence for the Bayes classifier. The road network and the Zoning Master Plan from the PDM were used in the post-classification, to reclassify pixels. The author concluded that the proposed method improved the Overall Accuracy (> 97%) of the classes where there was statistical information available.

Studies that apply the methods discussed in this and in previous sections, as well as studies that apply combinations of these methods, are summarized in Table 4. Only studies with three or more urban LULC classes, and which report quality indices of the produced maps, are presented.

Table 4. Studies on LULC maps having three or more urban classes and quality report

Classification Approach and Algorithms	Data	Thematic accuracy	Reference
Supervised classification			
Max. Likelihood applied on multi-temporal fusion images.	IKONOS	Overall: 81.0% Kappa: 77.8%	Bussios et al., 2004
Parallelepiped method to generate an urban land use map and, where there were classes overlapping, the Max. Likelihood was applied.	IKONOS	Overall: 83.0% Kappa: 77.0%	Davis and Wang, 2002
Neural Network with supervised training.	Landsat TM	Overall: 93.0%	Erbek et al., 2004
Neural Network with unsupervised training.	Landsat TM	Overall: 84.7%	Aitkenhead and Aalders, 2008
Use of textures			
GLCM to generate images of homogeneous texture from Landsat, and Max. Likelihood for classifying the image resulted from merging textural images with SPOT-Pan.	SPOT-Pan, Landsat TM	Overall: 88.3% Kappa: 88.2%	Kiema, 2002
GLCM to generate texture images, and a supervised classification by stepwise discriminant analysis applied only to the spectral bands and to the spectral and textural bands, for comparison.	SPOT 5 (simulations)	Overall: 94.1% Kappa: 92.0%	Puissant et al., 2005
Comparison of the maps produced by the GLCM, Gray Level Diff. Histogram and Sum and Diff. Histogram using the spectral and textural bands.	SPOT-XS	Overall: 86.0%	Shaban and Dikshit, 2001
Hybrid Classification (Sub-pixel/pixel)			
Linear SMA to obtain the sealed area, and rule-based approach based on the integration of impervious surface and population density images for further classification into land use map.	Landsat ETM+, Census data	Overall: 83.8%	Lu and Weng, 2006
SMA to identify pure training areas and Decision Trees classifier for land use classification.	IRS-1C	Overall: 89.5% Kappa: 87.9%	Rashed et al., 2001

Classification Approach and Algorithms	Data	Thematic accuracy	Reference
Use of ancillary data			
Imagery fusion, orthorectification and stratification using a DTM, and supervised classification based on fuzzy logic.	SPOT 3 Pan, SPOT 4, DTM	Overall: 83.6% Kappa: 80.1%	Doxani and Stamou, 2004
Fusion image classified by a Neural Network and post-classified using rules and fuzzy logic based on ancillary data.	Landsat TM, IRS-1D Pan, DEM, Topographical and geological maps, PDM, subsidiary schemes	Correlation coef.: 88.7%	Tapiador and Casanova, 2003
Census data in tabular and surface format were used to modify Max. Likelihood classifications through stratified class and in terms of assisting the selection of training samples and contextual post-classification sorting.	SPOT HRV, Landsat TM, Census data	Kappa: 73.7%	Mesev, 1998
Hybrid Classification (Supervised, unsupervised, use of context information)			
Max. Likelihood for land cover mapping. Then spatial texture was combined with ancillary data sets in an expert system to perform post-classification sorting of the initial land cover.	Landsat TM, Land use map, Texture image, DEM	Overall: 85.2%	Stefanov et al., 2001
Hierarchy tree classification for land cover mapping considering contextual information. Spatial analytical functions were then applied to improve the accuracy of the land-use classification. The unsupervised ISODATA classification based on characteristic density map was employed to further improve the classification accuracy.	IKONOS	Overall: 94.5% Kappa: 93.0%	Zhang et al., 2004
Supervised classifiers at the pixel level and Neural Networks to obtain the initial land use map. SMA and GLCM used to reclassify the misclassified areas.	SPOT 5 HRG	Overall: 80.3% Kappa: 78.1%	Gaspar, 2007
Max. Likelihood for an initial classification of the land cover map, followed by its reclassification into a land use using a frequency based contextual classification and the Min. Distance classifier.	SPOT HRV	Kappa: 70.0%	Treitz et al., 1992

3.6 OBJECT-ORIENTED CLASSIFICATION

The heterogeneity of complex landscapes, like the urban ones, produces great spectral variability within the same LULC class. With the pixel-based traditional classifiers, each pixel is individually grouped in a given class. The result will probably have too much misclassified areas given the expected large spectral variability. Alternatively, approaches based on objects are more able to work with the high heterogeneity found in complex landscapes (Blaschke and Strobl, 2001; Benz et al., 2004).

The concept of GEOBIA image classification was introduced in the 1970s, but it was abandoned in favor of pixel-based classifiers due to the easier implementation of the latter. GEOBIA did not gain popularity until a few years ago (since 2000), thanks to advances in computer hardware, software, and image interpretation theories, and to refined spatial resolution of imagery (Blaschke, 2010). This popularity is attributed largely to the release of commercial image analysis software packages such as eCognition (in 2000) and Feature Analyst (in 2001) (Figure 20). Prior to the advent of these tools, GEOBIA was very difficult to accomplish (Gao, 2009).

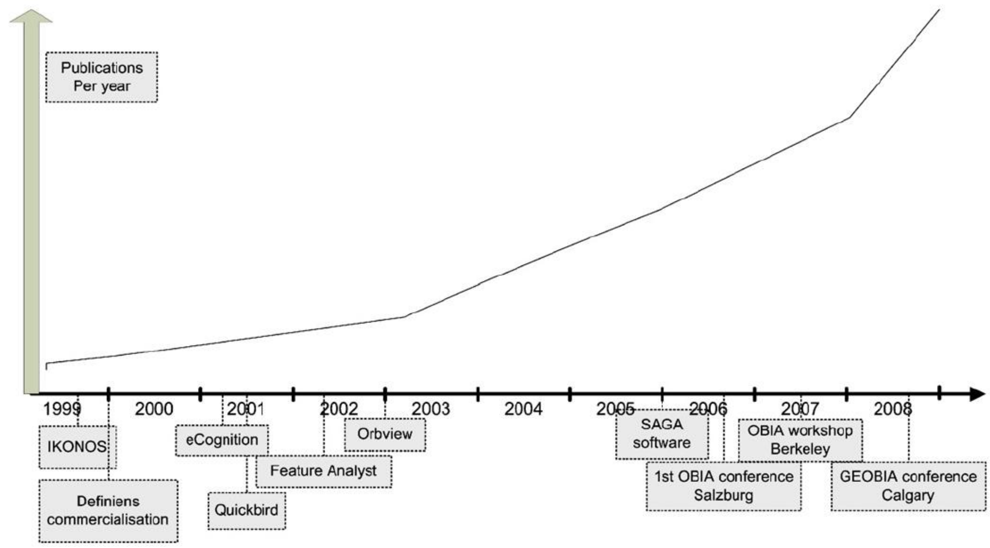


Figure 20. GEOBIA's literature schematic development and some triggers associated (source: Blaschke, 2010)

GEOBIA breaks down the image analysis process in two stages: the first involves a coarse segmentation of the image into a set of discrete regions, each delimiting a homogeneous area. Secondly, the main class of land use is inferred from the classes associated with groups of one or more regions based on spatial characteristics, textural and patterns analysis of land cover (Barnsley and Barr, 1996). In the GEOBIA approach, it is possible to develop and apply semantic rules based on physical parameters or knowledge about the relationship between objects.

GEOBIA classifiers have performed better than the traditional ones at the pixel level, particularly with higher spatial resolution data (Caprioli and Tarantino, 2003; Blaschke et al., 2005; Lu and Weng, 2007). The concept behind GEOBIA is that information relevant to the interpretation of an image is not represented in single pixels but in meaningful image objects, which reflect real patterns and their mutual relations (Chen et al., 2003b). The construction of these image-objects is based on the concept of spatial patchiness. A landscape object is a patch, defined as a discrete spatial unit having a certain minimum extension and differing from its surroundings in nature or appearance, like size, shape and internal consistency (Wiens, 1976; Kotliar and Wiens, 1990). Therefore, the partitioning of the image into sets of useful objects is key to the success of the automatic image analysis (Gorte, 1998; Baatz and Schäpe, 2000; Blaschke et al., 2005). One possible method to accomplish such partitioning is the application of segmentation algorithms, which break the image into spatially continuous, distinct and homogeneous regions (Blaschke et al., 2004). The following section describes some techniques for digital image segmentation and presents its theoretical foundation.

3.6.1 IMAGE SEGMENTATION

The human vision is able to detect objects and classes of objects in an image. In reproducing this cognitive process, the first stage is the image segmentation. The segmentation performs the subdivision of the image into homogeneous regions (i.e., the image segments), without attempting to classify them. Afterwards, the analyst can associate spectral information, or other information, to each region, in order to produce a classification.

There are many segmentation techniques applicable to EO data. The most relevant ones for EO data analysis are pixel, edge and region based methods (Blaschke et al., 2004).

Pixel-based segmentation

Grey level thresholding is the simplest image segmentation process. The process starts with the selection of a threshold value or range of values, consistent with the level of brightness of the elements to be extracted from the image. The simplest method results in a binary mask, with a value of 1 for the objects that meet the threshold, and 0 for others. This type of segmentation is usually applied to generate masks for further analysis. More complex methods include adaptive thresholding, band-thresholding, multi-thresholding or semi-thresholding. Correct threshold selection is crucial for successful segmentation. There are different strategies to select the best threshold value: based on the histogram shape, optimal thresholding, multispectral thresholding or hierarchical thresholding. Examples of applications include vehicles' detection and counting (Alba-Flores et al., 2004) or identification of urban objects (Zhao et al., 2005).

Edge-based segmentation

The aim of these algorithms is to find boundaries between image regions. The segments are defined as the areas within the region's boundaries. These boundaries are perceived as places where there is a sharp change in values (color, context, etc.). Generally, the edge detection includes three steps: filtering (to reduce the noise in the image), improvement in contrast (to reveal local variations) and detection (by application of linear change threshold and subsequent combination of edges into edge chains that correspond to the boundaries in the image). Applications include the detection of agricultural fields (Rydberg and Borgefors, 2001), the detection of buildings' limits (Selvarajan and Tat, 2001) or the extraction of road streets (Jin and Davis, 2003).

Region-growing segmentation

While the objective of the previous method is to detect boundaries between regions, the region-based segmentation is intended to build these regions directly. The main criteria for segmentation in region-growing is homogeneity of regions. The aim is to divide the image into regions of maximum homogeneity, using grey levels, color, textures, shape, models, etc. These algorithms can be divided into region growing, split and merging techniques, and their combinations. In all, the selection of the homogeneity criteria is crucial. The region growing segmentation starts by choosing an arbitrary seed pixel and comparing it with neighboring pixels. A region grows from the seed pixel by adding in neighboring pixels that are similar, increasing the size of the region. When the growth of one region stops, another seed pixel is chosen which does not yet belong to any region and the process starts again. This process continues until all pixels belong to some region. The merging operation is based on a homogeneity criteria or a combination of size and homogeneity. Examples of applications include change detection (Hazel, 2001), identification of agricultural areas (Evans et al., 2002) and identification of areas with different land uses (Chen et al., 2003b).

Region growing algorithms include: region merging, region splitting, and combination of both. The **region merging** algorithms begin the segmentation using regions of 2x2, 4x4 or 8x8 pixels. Region descriptions are then based on their statistical grey level properties. A region description is compared with the description of an adjacent region: if they match, they are merged into a larger region and a new region description is computed; otherwise regions are marked as non-matching (Nagabhushana, 2006). Merging of adjacent regions continues between all neighbors, including newly formed ones. If a region cannot be merged with any of its neighbors, it is marked 'final' and the merging process stops when all image regions are marked.

Region splitting is the opposite of region merging. It begins with the whole image represented as a single region (note that this situation does not usually satisfy the condition of homogeneity). The existing image regions are subdivided (split) until all of the above mentioned conditions of homogeneity are sutisfied. A combination of splitting and merging may result in a method with the advantages of both approaches (Salih, 2001).

Split-and-merge approaches operate using pyramid image representations. Regions are square-shaped and correspond to elements of the appropriate pyramid level (Nagabhushana, 2006). If a region in a given level is not uniform, it is divided into four sub-regions (quad tree), resulting, in the level below, in elements with higher resolution. If, however, on the same level of the pyramid, there are regions with similar homogeneity, they are clustered into one region, which will be represented in a higher level. One of the main disadvantages of this method is the assumption of a quadratic form for the regions, which does not always fit the image. Areas of applications include analysis of video images (Cortez et al., 1995), analysis of aerial photographs (Yang and Lee, 1997), extraction of roads from IKONOS images (Lee et al., 2000) or land cover analysis (Lucieer, 2004, Gao et al., 2007).

Another example of region-based segmentation algorithm is the **watershed transform**, establishing an analogy with the water-flow process in a topographic surface. In this context, an image band can be seen as a topographic surface where pixels with high values corresponding to peaks, and pixels with low values correspond to valleys. If a 'drop' falls anywhere in this area, it would tend to flow to a lower elevation until reaching a local minimum. The accumulation of water in this local minimum reveals the catchment basin, and all the dots/pixels that drain into a common basin belong to the same watershed. A disadvantage of this method is the over-segmentation, which is directly related to the large number of minima in the original image that can be caused by noise of the image itself. Applications include the assessment of damage caused by earthquake in urban areas (Sümer and Turker, 2006), identification of trees (Kubo and Muramoto, 2005) or mine field detection (Faur et al., 2006).

Generally, the segmentation of remote sensing images provides only initial information revealing the spatial pattern at a given scale. The segments produced by fine segmentation may not represent something meaningful at a more coarse scale. The same is true in most coarse segmentation, in which segments may have no meaning at a larger map scale. This implies that the segments in an image represent objects which are not meaningful at all scales. The extraction of meaningful image objects needs then to take into account the scale of the problem to be solved (Baatz and Schäpe, 2000). Thus, to work the entire spatial pattern available in a standard image, and its dynamics, it is necessary a multi-scale or multiresolution approach (Chen et al., 2003b).

Baatz and Schäpe (2000) propose a new algorithm called **multiresolution segmentation**. The procedure for the multi-scale image segmentation presented here can be described as a region merging technique. It starts with each pixel forming one image object or region. At each subsequent step a pair of image objects is merged into one larger object. The merging decision is based on local homogeneity criteria. The homogeneity criterion is not only a 'fit' or 'not fit' decision. A "merging cost" is assigned to each possible merge, representing the degree of fitting. For a possible merge the degree of fitting is evaluated, and the merge is performed if it is smaller than a given 'least degree of fitting'. The procedure stops when there are no more possible merges. A small 'least degree of fitting' allows fewer merges than a larger one. Therefore the size of the resulting image objects will grow with the 'least degree of fitting' value. Due to this property, the parameter is termed as the *scale* parameter (Baatz and Schäpe, 2000). Usually, the user has to decide the specific scale at which to segment an image into objects. However, this search process can be very subjective because it is highly dependent on the interpreter's experience (Wang et al., 2004b).

The aggregation of small objects into larger objects results in hierarchical levels of segmentation, which correspond to different resolutions. The objects created are sub or super-objects in a given level, because each object is generated based on their horizontal neighbors (within the same level) and vertical (inter-levels). Consequently, it creates a hierarchical network of objects with defined topology, where the limit of a super-object (larger object) is consistent with the limits of its sub-objects (smaller objects). Thus it represents both structures at different scales, which can be classified based on their hierarchical relationships (Figure 21).

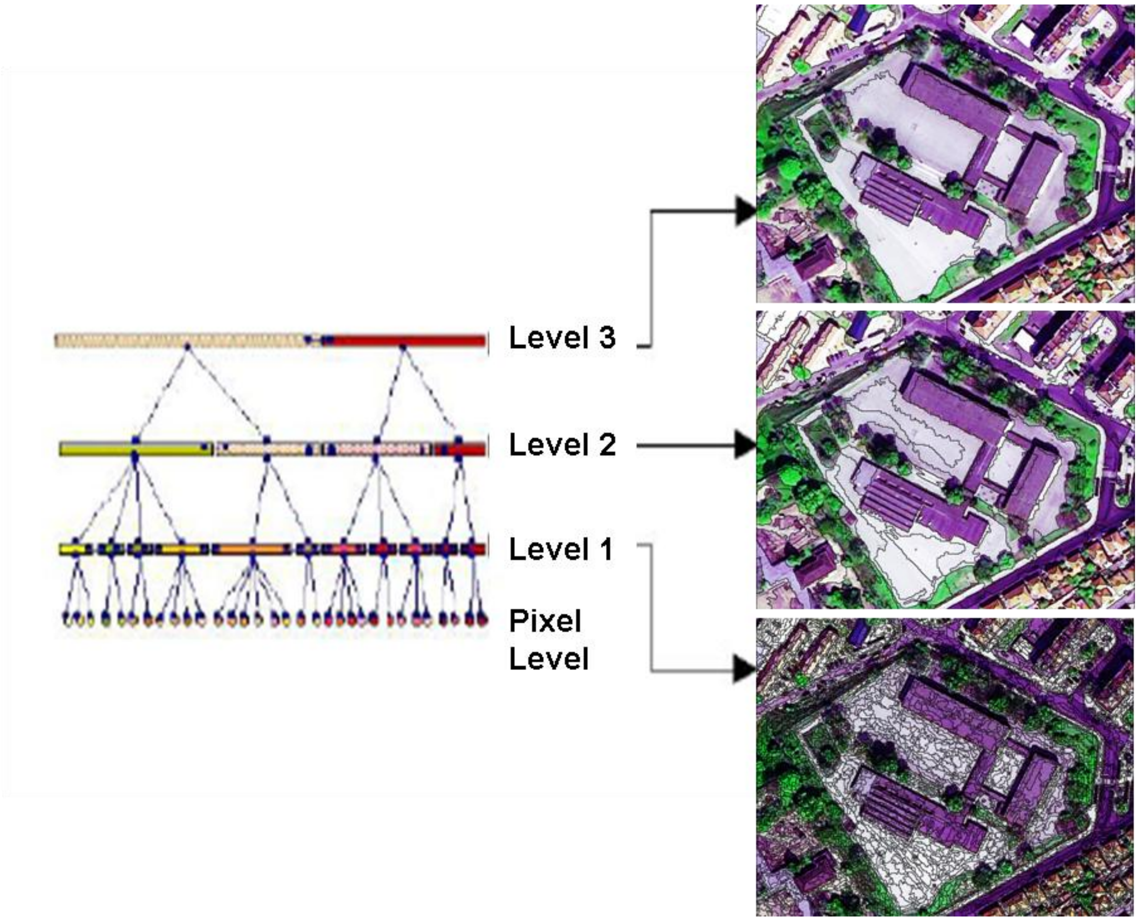


Figure 21. Hierarchical network of segments produced by multi-resolution segmentation of VHR image

The mechanism of human visual analysis provides a good basis for the multi-resolution segmentation: firstly it tends to generalize the images in homogeneous areas, and then to characterize them carefully (Gorte, 1998). Our vision can act in two ways. On one hand, we can have a general view - when we stop focusing on image details and look at all its extension, our perception shifts from the small elements to larger ones. On the other hand, we can focus in, when moving from the overview to detail, by zooming in the micro-elements at the expense of macro-elements. According to these two scenarios, a multi-resolution segmentation can follow two strategies: *Bottom-up* (simulating the process of generalization) or *Top-down* (simulating the process of focus).

There is no standard method for assessing the quality of segments produced by a segmentation algorithm. Haralick and Shapiro (1985) presented a qualitative method for this assessment: “the targeted areas of an image should be uniform and homogeneous with respect to characteristics such as levels of grey or texture. The interior of the regions must be simple and without small holes. Adjacent regions should have significantly different values regarding the characteristics on which it bases its uniformity. The boundaries of each segment should be simple, not abrupt, and should be spatially accurate."

Neubert and Meinel (2003), Meinel and Neubert (2004), Neubert et al. (2006), Neubert et al. (2008), Neubert and Herold (2008) present comparative studies of 24 segmentation algorithms applied to VHR images. To assess the quality of the segmentation produced, in addition to visual analysis, it was also carried out a geometric comparison of reference areas, based on spatial metrics. The authors concluded that there is more than an interesting approach in this area of research. In these studies, the software packages that obtained the best results were eCognition 3.0, Definiens Developer 7.0, Infopack (v1.0 and v2.0), EDISON, EWS and HalconSEG.

The segmentation phase, as described previously, does not classify each segment. Segmentation only subdivides the image into homogeneous areas (segments). Afterwards, these segments must be classified. The fact that the segments are objects, and not individual pixels, means that in the classification stage other characteristics besides the spectral information should be used, namely: shape, size, texture, hierarchy and neighbor relations. The next section describes the process of classification of objects into classes of information.

3.6.2 CLASSIFICATION OF OBJECTS

After segmentation, each homogeneous area (segment) of the image is a unit of analysis, for which a number of characteristics can be calculated and used in its classification. The classification can thus use the spectral values and texture of objects and their spatial properties: size, shape, orientation, average or standard deviation of brightness values of an image object, border length, density, etc. Based on these characteristics, new features can be built using different arithmetic operations (e.g., vegetation indices). Consequently, the classification of objects can use a wide range of spatial variables, textural and/or contextual.

Once the spectral and spatial attributes of each polygon are selected, they are used as input for a classification algorithm. Strategies for classification may include supervised classifiers (e.g., Maximum Likelihood or Minimum Distance), classifiers based on fuzzy logic, expert knowledge, decision rules, or hybrid classifiers. The classification is usually very fast since objects (i.e., polygons) are classified instead of single pixels.

Pixel-based classifications usually appear pixelized (salt and pepper effect), whereas object-based classifications can appear fractal (Jensen, 2005).

3.6.3 IMPLEMENTATION ENVIRONMENTS

The increasing number of sensors that capture large volumes of remotely sensed data, with higher spatial resolutions than ever before, favored the development of automated image processing tools that can quickly and reliably extract meaningful geospatial information for numerous scenarios (O'Brien and Irvine, 2004). There are different approaches to extract geo-information based on object-based methodologies. Feature extraction algorithms and object-based classifiers are two alternative approaches. The following sections characterize these methods based on the algorithms and parameters implemented in commercial software. Several image-processing software packages already support object-based classifications. Examples include: Feature Extraction tool for ENVI, ERDAS's IMAGINE Objective module, FeatureObjeX tool for PCI Geomatics, eCognition, and Feature Analyst tool available for ERDAS IMAGINE, ArcGIS and Geomedia. This section introduces Feature Analyst and eCognition.

Feature Analyst

Feature Analyst (FA), which is a feature extraction designed for use as an extension for GIS/image processing software such as ArcGIS or ERDAS IMAGINE, was developed by Visual Learning Systems (now Overwatch Systems), with funding from NASA and the U. S. Department of Defense. The application tool was first released in 2001 (FA v2.1). Currently, FA v5.0 is available. FA uses a machine-learning algorithm based on training samples, to achieve automated feature extraction (Visual Learning Systems, 2005).

FA uses a combination of object segmentation and neural network technology. The FA classification setup is similar to a standard supervised classification, where the user needs to supply training sites of each feature class of interest. Also an unsupervised extraction is available. The FA classification scheme incorporates a contextual classifier, defined by the user, according to the configuration of the image features to be extracted. Also, knowledge-based criteria such as whether the feature of interest is long and narrow (e.g., roads) or small and boxy (e.g., buildings) can be specified, as well as a minimum area to be extracted. In the supervised mode, the program analyzes the training set and creates distinct segments based on the training data and the inputted knowledge. The results of this first pass can be corrected and added back into the system as knowledge, in an interactive learning process.

Compared with a traditional land-cover classifier, FA has three major advantages. First, allows the use of a foveal representation, where the learning algorithm is given a region of the image with high spatial resolution at the centre (where the prediction is being made) and a lower resolution away from the centre. Thus, it provides contextual spatial information to the learning algorithm while greatly reducing the amount of data given to the learner. Second, FA addresses image clutter with a hierarchical approach that allows the classifier not only to learn from the user input and return similar objects but also to improve classification results by mitigating clutter and retrieving missed features (Visual Learning Systems, 2005). Third, allows to train and extract only features from the desired classes, whereas on traditional classification procedures, at least two classes must be defined, the class of interest and the remainder. In addition to automating the extraction of single features, Feature Analyst also offers tools for creating multi-class extractions (Optiz and Blundell, 2008).

eCognition

eCognition was the first commercial software developed for digital images analysis fully based on object-oriented techniques. It was released in 2000 by Definiens Imaging GmbH of Germany (Baatz and Schäpe, 2000). eCognition operates on the following basis: multi-resolution segmentation of image objects based on homogeneity criteria (defined in terms of scale, color, shape, smoothness and compactness) and subsequent classification using attributes such as color, shape, hierarchy, texture and spatial context. The classification is preformed through a class-hierarchy that can be understood as generating a rule-base wherein the user determines physical and semantic properties typical for the objects of a certain class. The software offers two basic classifiers: Nearest Neighbor classifier and fuzzy membership functions. Both act as class descriptors. The Nearest Neighbor is a traditional supervised classifier that uses training samples to map each class while fuzzy membership functions describe intervals of feature characteristics wherein the objects do belong to a certain class or not by a certain degree. A class then is described by combining one or more class descriptors by means of fuzzy-logic operators, by means of inheritance, or a combination of both (Hofmann, 2001b).

The success of an image classification depends on many factors. The availability of high-quality remotely sensed imagery and ancillary data, the design of a proper classification procedure, and the analyst's skills and experience are the most important ones (Lu and Weng, 2007). Table 5 describes several studies that compare maps produced by different digital classifiers and by different classification approaches (pixel or object). Only studies that include urban classes and that have their conclusions validated trough an accuracy assessment procedure are presented.

Table 5. Comparative studies of digital image classification methodologies, with one or more urban land cover class and quality report

Algorithms	Data	Study area	Urban classes	Thematic accuracy	Reference
Neural Network Hard classif.	IKONOS	Bath, UK	2 Classes	RMSE 0.152 RMSE 0.235	Tatem et al, 2001
Decision Tree GEOBIA	IKONOS	Dresden, Germany	7 Classes	Overall 89.6% Overall 89.6%	Meinel et al., 2001
SMA and Decision Tree Min. Distance Max. Likelihood	IRS-1C	Cairo, Egypt	5 Classes	Kappa 88.0% Kappa 60.0% Kappa 45.0%	Rashed et al., 2001
Neural Network GEOBIA	IKONOS	Pickering, Canada	3 Classes	Overall 67.4% Overall 74.4%	Mittelberg, 2002
Parallelipiped Min. Distance Max. Likelihood GEOBIA	Landsat ETM+	Zonguldak, Turky	1 Class	Kappa 53.2% Kappa 49.9% Kappa 55.8% Kappa 76.6%	Oruc et al.,2004
Neural Network Max. Likelihood	Landsat TM	Ikitelli, Turky	2 Classes	Kappa 84.2% Kappa 92.6%	Erbek et al., 2004
Max. Likelihood GEOBIA	QuickBird	Shenzhen, China	1 Class	Kappa 52.9% Kappa 88.3%	Cao and Ke, 2006
Max. Likelihood Markov Random Field (modified)	SPOT-XS	Blida, Algeria	3 Classes	Kappa 72.6% Kappa 84.2%	Khedam and Belhadj, 2004
Max. Likelihood GEOBIA	ASTER	Mongolia, China	1 Class	Overall 46.5% Overall 83.3%	Yan et al., 2006
Max. Likelihood Linear SMA Fuzzy logic SMA	Landsat ETM+	Houston, USA	3 Classes	Kappa 27.9% Kappa 40.9% Kappa 26.8% Kappa 77.3%	Tang, 2007
Max. Likelihood GEOBIA	Landsat ETM+	Manas County, China	1 Class	Kappa 66.3% Kappa 87.7%	Qian et al.,2007
Min. Distance GEOBIA	Landsat ETM+	Kashan, Iran	1 Class	Overall 81.0% Overall 91.0%	Matinfar et al., 2007
Max. Likelihood GEOBIA	QuickBird	Lavras, Brazil	1 Class	Kappa 63.0% Kappa 76.8%	Bernardi et al., 2007
Max. Likelihood GEOBIA	QuickBird	Wuhan, China	4 Classes	Kappa 70.0% Kappa 77.9%	Huang and Ni, 2008
Neural Network Support Vector Machines Max. Likelihood	Landsat TM	Joshua Creek Watershed, USA	1 Class	Kappa 42.1% Kappa 71.0% Kappa 72.7%	Dixon and Candade, 2008
Supervised Unsupervised Fuzzy logic GIS post-processing	ALOS-AVNIR2	Tsukuba, Japan	3 Classes	Kappa 80.0% Kappa 71.0% Kappa 85.0% Kappa 87.0%	Thapa and Murayama, 2009

3.7 CHANGE DETECTION WITH SATELLITE IMAGES

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Updating the information on land surface allows understanding the interactions of economic, social, and environmental choices in land-use and land-management policies and decisions. Change detection techniques applied in EO data can be useful in several areas like assessing human impact on the territory (urban sprawl, deforestation), monitoring ecological communities (forest fire, wetland change) or damage assessment operations (drought or flood monitoring, desertification) (Figure 22). Updated information permits quantifying past interventions on the territory, leading to better decision making in the future.

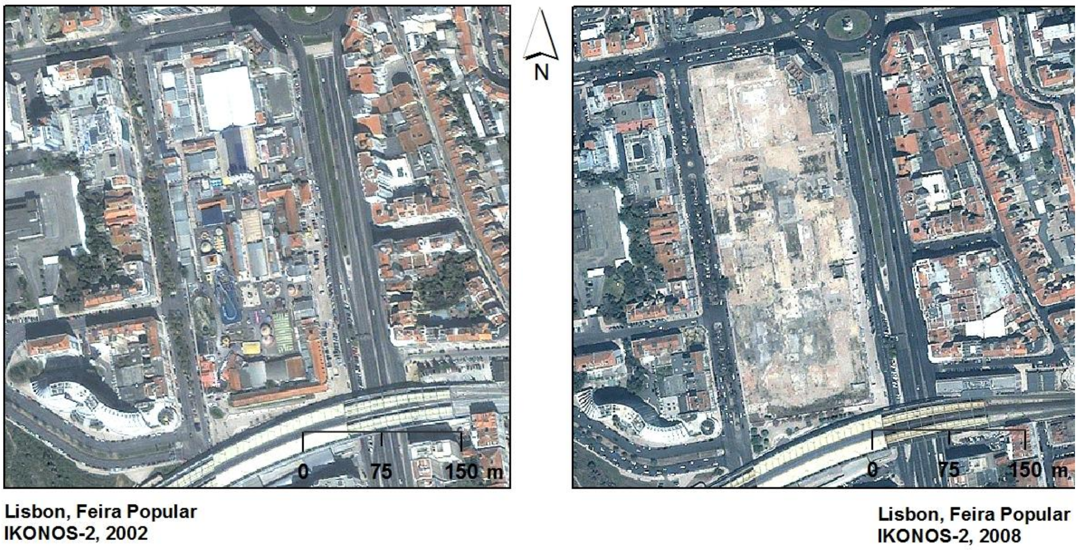


Figure 22. Land use land cover change due to building demolishing, in the city of Lisbon

In Portugal, at the local scale, the official cartography is produced under the framework of the PDM, which has a legal term of 10 years. Consequently, the municipal cartography is usually updated every 10 years, in the best scenario. In the municipality of Lisbon, for example, in 2010, the official cartography in use is still from 1994, since the new PDM is not yet approved. In municipalities with areas subject to strong urban pressure, that frequency of map updating is not compatible with the high rate of changes. The municipal cartography fails to represent the current reality, thus hindering decision-making on land planning, land use management and land conservation, as well as compromising policy delineation of human and economic activities, or even limiting efficient law enforcement.

Regular updating of municipal official cartography is very expensive and time consuming. This situation derives from two facts. In on hand, to be an official document, a map has to follow scale-specific technical specifications, imposed by the IGP, the institution that regulates the official cartography in Portugal. On the other hand, since the specifications are very detailed, the traditional framework based on aerial images, photogrammetry, and fieldwork, is the most common way of producing these maps. Consequently, the whole process of cartographic production requires a significant financial effort from the municipalities. A cartographic product based on satellite images, having less detail than the official cartography but with more frequent updating, can be used to complement the traditional cartographic framework, which is based visual interpretation of aerial photographs (Santos, 2003).

There are several advantages in using satellite images instead of aerial to update existing maps. First of all, a single satellite scene covers a large area (from less than 65 km^2 for OrbView-3 to more than 270 km^2 for QuickBird). Consequently, the cost of image acquisition may be reduced, and also the pre-processing time. One important factor is that remotely sensed images of a specific site can be collected with very short revisit time and in remotely locations. Consequently, it is possible to quickly update the existing cartography, also in areas that were previously too remote or too dangerous to reach using conventional aerial images. In well-mapped countries, such as Western Europe, detailed topographic databases have been (or are being) created using both field surveys and aerial surveys. Therefore, the main task of the national mapping agencies is the updating of the existing topographic databases rather than the creation of new topographic maps (Gianinetto, 2008).

Land cover can be induced by natural processe or by anthropogenic forces. Natural events such as extreme weather, flooding, fire, climate change, and ecosystem dynamics may also contribute to modifications upon land cover. However, the focus of this thesis is the urban environment, so the following sections will discuss change detection methodologies applied in that context.

3.7.1 NATURE OF CHANGE

Change detection includes two basic aspects: detect if a change occurred within the period under analysis, and what changed into what. The first aspect is a simple classification into change/no-change, whereas the later is related with the change direction: “from-to” class analysis. The proper understanding of the nature of the change and the principles that enable its detection and categorization usually encompass more sophistication than the simple detection of the change event itself (Coppin et al., 2004).

The study of land cover dynamics is a thematic analysis but also a spatial one. Changes in land cover driven by changes in land use can be categorized into two types: modification and conversion (Lambin, 2003). Modification is a change of condition within a cover type (e.g., dispersed urban area changed to compact urban area). Conversion, on the other hand, is a change from one cover type to another (e.g., from forest to bare soil). The classes can then change in their cover type (thematic change) but can also suffer spatial temporal modifications (geometric change). One change type is not independent from the other, and sometimes the two concepts (thematic and spatial change) overlap. Macleod and Congalton (1998) list four aspects of change detection:

- Detecting that changes have occurred;
- Identifying the nature of the change;
- Measuring the areal extent of the change;
- Assessing the spatial pattern of the change.

Raza and Kainz (2001), in an GEOBIA approach for modeling land use change, considered parcels as objects that can appear, disappear, transform, or change size, position, and shape in the database. In the case of two or more parcels, parcels can be subdivided or amalgamated. Blaschke (2005) suggested a framework which categorizes the geometric changes which may occur between the same object in two different data sets. Figure 23 illustrates the types of spatial changes that may occur on the same subject at different times based on the works from and Raza and Kainz (2001), and Blaschke (2005).

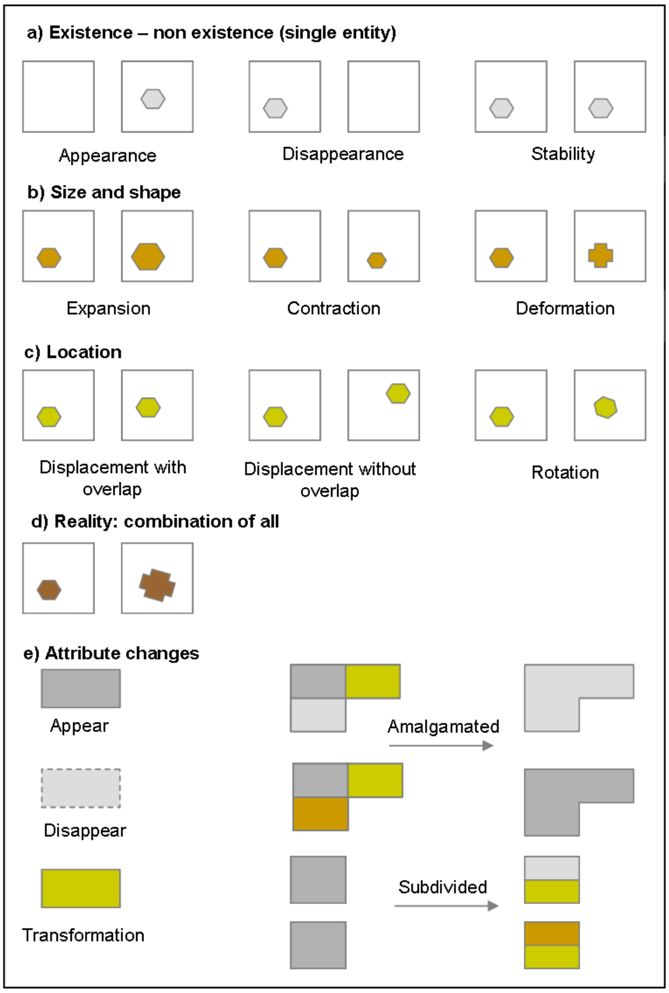


Figure 23. Typology of spatial and thematic changes in objects (adapted from Raza and Kainz, 2001, and Blaschke, 2005)

The fact that changes in spectral reflectance reflect changes in land cover is the basic premise for the use of satellite imagery to detect changes (Singh, 1989). However, to be correctly detected, the variations in spectral reflectance due to land change must be greater than the variations due to other factors. To minimize these external factors that may contribute to false changes in multi-temporal data, it is necessary to satisfy the following conditions (Yuan et al., 1999, Lu et al., 2004): (1) the images must be geometrically registered, (2) precise radiometric and atmospheric calibration or normalization, (3) similar phenological states between multi-temporal images, and (4) if possible, selection of the same spatial and spectral characteristics. Below is a discussion of each factor and its influence on the efficiency of change detection in multi-temporal images.

Registration of Multi-Temporal Images

It is necessary to ensure, in a multi-temporal study, that the location of pixels in different images is identical, i.e., that the pixel being compared at different dates is the same. This is achieved using geometric correction models which produce low values of RMSE. In a multi-temporal data set, usually an image is referenced to a map with a larger scale and a coordinate system. The other images are then registered to this reference image, to ensure the proper pixel alignment. In geometric correction, polynomial algorithms like PieceWise Linear (PWL) or spline interpolators (e.g., Thin-PLate spline - TPL) are built based on GCPs and the quality of the correction is judged by the RMSE result (see Chapter 2 for more details on image registration).

Arévalo and González (2007), studied several registration techniques on QuickBird images, and concluded that if the images are orthorectified before the registration, even if not very precisely, the polynomial adjustment yields good results, even for high-relief terrain and different viewing angles. But if no orthorectification is applied, the application of global methods (PWL or TPL) offers best corrections. However, the failure to perform the orthocorrection, due to the topography, leads to the permanence of geometric deviations which are reflected in the evaluation of differences in land cover images.

When comparing objects of different dates to identify changes, problems due to poor registration are more severe on pixel-based approaches (Blaschke, 2005). Roy (2000) showed that when a multi-temporal sequence of images is used, the errors of spatial mismatch may significantly exaggerate or, alternatively, mask the changes. Figure 24 illustrates, for an object, the difficulties in detecting real changes due to the geometric inconsistencies that result from poor data registration.

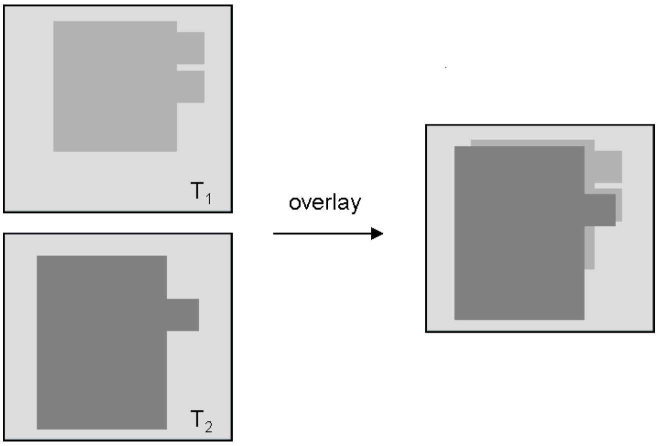


Figure 24. Overlay of two polygons representing the same object but in different times (T_1 and T_2). The close-up look (right) illustrates that next to an evident area of change, other false changes are due to spatial inaccuracies

Fuller et al. (2003) examined problems in the detection, measurement and characterization of land changes from satellite images. The authors tested if the combination of errors from two maps could result in incorrect change detection, using two maps produced by image segmentation and classification: the 1990 Land Cover Map of Great Britain (LCMGB), and the United Kingdom Land Cover Map (LCMUK), from 2000. The field surveys of 1990 and 1998–1999 recorded an overall change of 17%, being indicative of the level of change which the remotely sensed maps should detect. The accuracy of LCMGB is 80% and the LCMUK's is 85%. When comparing the two maps, a total of 16 classes, with spatial resolution of 25 m were analyzed. With a 17% change and the levels of accuracy estimated for LCMGB and LCMUK, there would be only a 57% agreement between two maps, and 43% of the combined map area would have recorded differences. Of the 43% difference, 17% were real change and 26% were due to errors. On the positive side, 98% of changes would have been mapped as such but only through a very substantial over-estimation of the change. Thus, for a simple post-classification comparison to be accurate, it must take into account the quality of the maps being compared.

Radiometric and Atmospheric Calibration or Image Normalization

Ideally, only the information that relates to the objects themselves is important for change detection. In multi-temporal studies, the radiometric correction is applied to make the brightness values comparable. If the study area is flat, the path radiance can be removed or a conversion of the original units (DN or radiance) for surface reflectance values can be made. It is also common to divide all the pixels by the cosine of the zenith angle to make the lighting conditions comparable. Another option is the radiometric normalization, which makes the disruptive effects between images equal, rather than removing them. This method consists of applying a linear model that transforms the values of brightness of a date into values that were obtained if the image had been acquired in the same conditions as the reference image. Please see section 2.4.2 for more details.

Similar Phenological States between Images

This condition is relevant when studying changes in the land cover in areas with vegetation. If an agricultural plot is being monitored to see if the same species is being cultivated, using satellite images, then the image dates should match (e.g., same week in two consecutive years), to assess the crop in the same state of phenological development. But while the choice of close dates may reduce the possibility of false changes, other environmental conditions such as rainfall or the intensity of forest fires, can delay or accelerate plant development.

Similar Spatial and Spectral Resolutions

The images used to detect changes should be obtained by the same sensor, in order to reduce adverse effects caused by the change of scale which may introduce false changes. Excluding the changes that may occur for failure to comply with the above conditions, the ones of interest vary with the level of processing invested in the analysis. Lu et al. (2004) classified the land cover change detection into 2 groups: detection of detailed "from-to" change and simple binary detection of change/no-change. Indeed, quantifying changes in land cover is rarely enough. Generally, information on LULC class before and after the change is required to allow analysis of the "from-to” phenomena.

Change Detection based on VHR Imagery

Besides the already mentioned situations that can affect change detection, when working with VHR images, other situations must be considered. In fact these sensors can acquire images with different view angles, thus showing different geometrical distortions (Figure 25). Variations of view angle make some image features corresponding to the same 3D object appear at different locations in the image pair resulting in false changes. Another problem is the presence of shadows, which also produce false changes due to shadow region variations. These do not constitute real changes in the scene.

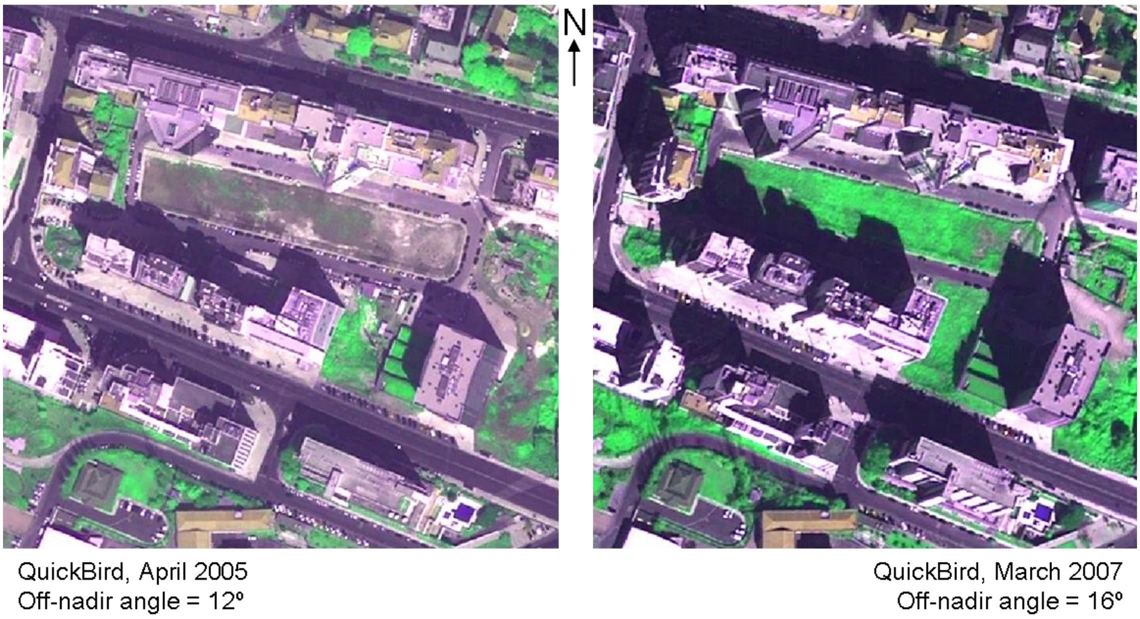


Figure 25. Images of the same site acquired in two different years, and with different view angles and satellite azimut

The shaded areas are usually left unclassified or simply classified as shadows (e.g., Shackelford and Davis, 2003), resulting in a significant loss of information on land features. One possible approach to overcome this problem is to use spatial information, such as adjacency relations, for the classification of shaded areas in this kind of images (e.g., Yuan and Bauer, 2006; Zhou and Troy, 2008; Dinis et al., 2010).

3.7.2 Techniques to Detect Changes in Satellite Images

Several techniques to detect land cover changes in satellite images are described in the literature. The following paragraphs present different categories of algorithms proposed by various authors.

Coppin et al. (2004) grouped change detection techniques in 10 categories: 1) post-classification comparisons, 2) composite analysis, 3) univariate image differencing, 4) image ratio, 5) bi-temporal linear data transformation, 6) change vectors analysis, 7) image regression, 8) multi-temporal spectral mixture analysis, 9) multi-dimensional temporal feature space analysis, and 10) hybrid and less frequent methods. The first 6 are the most common techniques, while others are less common and/or are in experimental stages.

Lu et al. (2004), in turn, grouped change detection methods into 7 categories: 1) algebra, 2) transformation, 3) classification, 4) advanced models, 5) approaches based on GIS, 6) visual analysis, and 7) other approaches. These techniques were classified as to its complexity and characterized regarding their main advantages and disadvantages. The simplest techniques are based on algebra (difference, ratio or images regression and subtraction of background information). Although easy to apply and reducing solar and topographic effects, they do not produce a detailed change matrix and require selection of change thresholds. The more complex categories based on classifications (e.g., neural networks) and advanced models (Li-Strahler model to reflectance, biophysical parameters estimation models), require many field data, or great control of atmospheric conditions during image acquisition, or just provide vegetation changes, or are not available in commercial software.

While most of the change detection techniques are focused on the level of processing - changed based on the original pixels values vs. classified data (Blaschke, 2004) - Hall and Hay (2003) grouped the techniques according to a system proposed by Deer (1998). Three approaches are identified, according to the level of image processing: pixel, feature and object level. The pixel approach refers to the numerical values of each band of the image or simple calculations between bands (e.g., image differencing or image rationing). Generally, it is not possible to assign a symbolic meaning from the pixel level without further analysis. The feature level is a more advanced stage of processing, which involves transforming the spatial and spectral properties of the image (e.g., Principal Components Analysis - PCA, or texture analysis of vegetation indices). Thus, the element may have a meaning in the real world (e.g., rates of vegetation in the radiometric field) or not (e.g., principal components in the radiometric domain). The object is the most advanced level of processing and involves more complex methods based on artificial intelligence, expert systems, or post-classification comparison (Blaschke, 2005).

Jensen (2005), in turn, distinguished 9 general classes of techniques: 1) detection of changes using the color composite, 2) multi-date image composite analysis, 3) image algebra, 4) post-classifications comparison, 5) multi-temporal analysis using a binary mask applied to date 2, 6) multi-temporal analysis using auxiliary information as date 1, 7) manual digitization, 8) change vector analysis, and 9) knowledge based systems. These techniques are described in the following sections. Jensen's classification (Jensen, 2005) was chosen for describing the change-detection methods in EO data, because it is one of the most used in the literature. The following sections describe each change detection technique.

Changes Detection Using Color Composition

This is a technique for visual detection of changes in individual bands that are loaded into specific color channels (blue, green and/or red). The advantages of this technique lie in the possibility of displaying two or three image dates simultaneously. Moreover, the analyst can incorporate texture, shape, size and patterns into visual interpretation to make a decision on the LULC change. However, it provides no quantitative information on changes (e.g., Crapper and Hynson, 1983, Jensen et al., 1993a), the results depend on the analyst's skill in image interpretation, and require further processing for map updating. Examples of studies that use this technique include Crapper and Hynson (1983), Virag and Colwell (1987), Jensen et al. (1993a) or, Aldakheel and Al-Hussaini (2005).

Multi-Date Image Composite Analysis

In this technique, all bands, or a selection of bands of the dates in question, is combined into a single data set. It is therefore a combined temporal-spectral analysis. The composite thus created can then be analyzed with different change detection techniques including PCA and multi-temporal classifications.

PCA, when applied to multispectral data, produces a series of linear transformations of the variables observed, resulting in a new data set of orthogonal variables. Each new variable (component) explains the highest variability in existing orthogonal data. The first component holds 90 to 95% of the total variance present in the original data while the subsequent components contain sequentially smaller values. The technique has the advantage of requiring only a classification. Furthermore, PCA is a technique that automatically removes subtle differences between two images (e.g., differences due to the atmosphere). Difficulties arise when one tries to interpret and classify each image component. It is a technique that depends on the analyst's skill, in identifying which component best represents the change, and selecting thresholds (Jensen, 2005). Examples of applications include the studies of Byrne et al. (1980), Fung and LeDrew (1987) or Kwarteng and Chavez (1998).

Multi-temporal classifications involve the combination of bands of different dates into a single data set. This set is then classified using supervised or unsupervised algorithms (e.g., Yuan et al., 1999). It is a simple technique of easy implementation. However, it is difficult to classify the types of change and the resulting matrix is incomplete (no information "from-to"). Another difficulty is the *a priori* estimation of class probability of occurrence. Examples include the studies of Bruzzone and Serpico (1997), Acharya (2002) or, Healey et al. (2005).

Image Algebra

Map algebra applied to remote sensing images includes algebraic manipulations of the reflectance values like image differencing. This technique involves computing the difference between reflectance values for a given band from two images. The resulting image represents the changes between the two images. The pixels that exhibit a change in its brightness will be positioned in the tails of image difference distribution, whereas the unchanged pixels are around the mean. However, this technique only identifies areas of change and no-change, providing no information on the change type. Studies with difference images for automatic detection of changes include Gong et al. (1992), Manavalan et al. (1995), and Lunetta et al. (2002).

Another image algebra method is computing the ratio between the values of pixel in the same band, or sets of bands, from co-registered images from different dates (e.g., vegetation indices). If the pixel does not change, then the ratio is near the unit. If changes occurs, then the ratio should be higher or lower than the unit, (e.g., Nelson, 1983; Prakash and Gupta, 1998; Masek et al., 2000). This technique reduces the impact of Sun angle, shadows and topographic effects.

The main advantages of these techniques are their simplicity. But no detailed information on the type of change is given, selection of thresholds is required and they are highly sensitive to image misregistration. Examples include the studies of Santos et al. (1999), Chen and Chang (2005) and Gong et al. (2008).

Post-Classification Comparison

It is one of the quantitative techniques most used to detect changes (Jensen, 2005). This technique requires classification of each image date, adopting a common nomenclature. Changed areas are simply those areas which are not classified the same at different times. Jensen (2005) advises performing the geometric correction only after the classification in order to avoid changes in the brightness values due to resample. For the method to be valid, the individual maps must have a high thematic and positional accuracy.

The comparison of maps minimizes the need for atmospheric correction since only already classified data is compared. Another advantage is the knowledge of the type of change occurred. However, it always involves two or more classifications, and their accuracy will influence the quality of change detection. Examples of studies with post-classification comparisons include Ramadan et al. (2004), Nichol and Wong (2005), Yuan et al. (2005), Rymasheuskaya (2007) or, Zhou et al. (2008).

Multi-Temporal Change Analysis Using a Binary Mask Applied to Date 2

This technique is very effective to detect changes. Initially, a classification is applied on image from date 1. Then, one band from both images (e.g., the red band from date 1 and 2) is analyzed using algebra operations. The thematic map is produced by applying a change threshold. The changed areas are used to build a binary mask that is overlaid on the image from date 2. Only the pixels of areas changed between the two dates are classified in the second image. By excluding unchanged pixels from classification, it reduces classification errors and effort.

This technique requires many steps, but can reduce the omission and commission errors, and provides detailed information about which classes changed ("from-to" changes). However, its success depends on the quality of the mask with the binary change information and requires selection of thresholds to implement classification. Examples of applications include Lo and Shipman (1990), Jensen et al. (1993b), Sader (1994), Coppin and Bauer (1996), Lu et al. (2005) or, Im et al. (2007b).

Multi-Temporal Analysis Using Auxiliary Information as Date 1

In this technique, the information from date 1 is not a satellite image but rather a thematic map. The most common example of application is to update existing digital maps in GIS. For date 2 there is an image that is classified and compared with the existing map.

The technique allows identifying the changes "from-to", regarding only the classification of one image. It also allows access to ancillary data to aid interpretation and analysis and has the ability to directly update land-use information in GIS (Lu et al., 2004). However, the same classification system must be used and a good registration between the map and the image is required. Selecting data with different levels of quality and from various sources often degrades the results of LULC change detection. Examples include Lo and Shipman (1990), Yeh and Li (2001), Prol-Ledesma et al. (2002), Frauman and Wolf (2005), and Wang et al. (2006).

On-screen Digitization

Visual interpretation followed by manual digitization is a very common method to produce maps from images. An efficient process is to view both image dates side by side, and geometrically registered, so that the digitization of a polygon in an image appears in the same place in the second image. CLC is an example of a project based on photo-interpretation of changes between two time periods.

The main disadvantage of the method is that the whole process is subjective and time consuming. Examples of applications are the studies of Sunar (1998), Slater and Brown (2000), and Loveland et al. (2002).

Change Vectors Analysis

Multispectral data can be represented in a vector space with n dimensions, where n is the number of bands. A pixel is represented by a point in that vector space, where its coordinates are the brightness values of the corresponding band. Thus, the values associated with each pixel define a vector in multidimensional space. If a pixel changes between two dates, it is then possible to define a vector that describes the change by subtracting the vector from the 1st date with the vector from the 2nd date. This vector is called spectral change vector, and is characterized by a value of intensity and direction. If the intensity of the vector exceeds a certain value then it corresponds to a change pixel. Moreover, the direction of the vector contains information about the type of change. This technique is capable of processing any number of spectral bands and to producing detailed change detection information. However, it requires the radiometric correction of images, to avoid false changes. Examples of applications include the work of Lambin and Strahler (1994), Johnson and Kasischke (1998), and Chen et al. (2003a).

Knowledge-Based Systems

These techniques include the application of intelligent systems such as Decision Trees or Neural Networks. Sample texture measures between images can be used to train the expert systems in order to generate change rules "from-to". The rules are then compiled and used to produce the change map (e.g., Im et al., 2005). However, in Neural Networks the nature of hidden layers is unwell known. Also a long training time is required. Examples include applications developed by Wang (1993), Huang and Jensen (1997), Civco et al. (2002), Liu and Lathrop (2002), and Im et al. (2005).

Selection of Change Threshold

The application of the previous methods, except those based on classification comparison, requires the decision of where to set the threshold that separates the changed from the unchanged areas. This threshold can be obtained in two ways (Singh, 1989). The first method involves the manual selection or interactive trial-type error, until the result is satisfactory. Another method uses statistical measures taken from the image. Usually, values of standard deviation are selected. Figure 26 illustrates this criterion for a difference image, which follows a normal distribution. Within the range given by $\mu \pm c\ \sigma$ (where μ is the average, c a constant and σ the standard deviation of normal population), are those pixels that have not changed. Above and below that (tails of the distribution), are those pixels that changed between images.

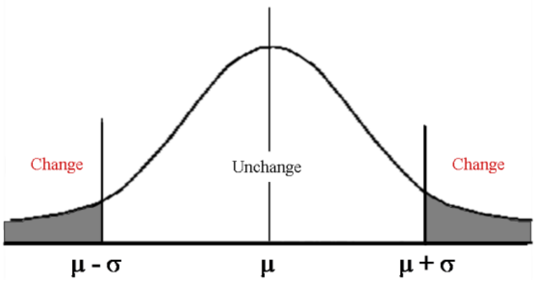


Figure 26. Histogram of a difference image and the change threshold of one standard deviation from the mean

The major disadvantage of thresholds selection is that its evaluation is very subjective and depends on the study area. Also resulting differences might include external influences caused by atmospheric conditions, Sun angle, soil moisture and phenological differences in addition to true land-cover change.

In order to overcome these disadvantages, Metternicht (1999) proposed the use of fuzzy logic to replace the change threshold. The first step involved setting up an image of change (obtained by image differencing or ratioing), followed by adapting the membership function of the fuzzy model to fit the shape of the histogram characterizing the change image. Then a linguistic scale was adopted to subdivide the fuzzy membership function, representing the degrees of possibilities for change. The final step assigned a grey scale to the sliced change images.

Bruzzone and Prieto (2000) proposed a technique to automatically select the change threshold in differencing images. The analysis was based on minimizing the Bayes cost and defining a threshold that minimizes the overall probability of false change detection. The methodology allowed the generation of maps in which the overall change-detection cost was minimized, i.e. the more critical kind of error was reduced according to end-user requirements.

Which method is best suitable for a specific study area is a question that remains unanswered in the scientific literature. Digital change detection is a difficult task to perform accurately, and unfortunately, many of the studies concerned with comparative evaluation of these applications have not supported their conclusions by quantitative analysis (Singh, 1989). The selected method then depends on an analyst's knowledge of the change detection methods, the image data selected, and the characteristics of the study area (Lu et al., 2004). Generally, it is common to compare different change detection techniques in order to choose the best result based on accuracy assessment. The most used methods are image differencing, PCA, change vector analysis and post-classification comparison.

3.8 CONCLUSIONS

This chapter reviewed the characteristics of the urban objects and the techniques for mapping and monitoring it using remote sensing data. At this point, one can drawn conclusions about what is the data source indicated for urban mapping, the methodologies used to extract urban features and to update existing cartography.

3.8.1 DATA SOURCE FOR URBAN MAPPING

Most elements in the urban environment are characterized by a high spectral heterogeneity that is related to the object's size. On one hand, objects in complex urban environments (buildings, streets, cars) are generally smaller than the objects found in rural areas (agricultural fields, forests, lakes) (Small, 2003). Moreover, cities are not composed solely of artificial objects that result in soil impermeabilization. Additionally there are also co-natural elements such as parks, gardens, lakes or bare soil. When this information is captured by digital sensors aboard satellites, the spatial resolution (i.e., the minimum size of an identifiable element in the field) of these systems will determine the greater or lesser presence of mixed pixels, i.e., pixels with spectral information derived from several land cover classes. And while the existence of mixed pixels varies with the size of the pixel, it is always higher in urban (Hoster, 2007).

When characterizing the urban environment, the spatial resolution with which this phenomenon is captured is a crucial variable. Consequently, the choice of satellite imagery of high-resolution is the most appropriate as a primary source of data for the extraction of thematic information. In this type of images, coupled with high spatial resolution, is the perception of shapes and relationships between objects. All this spatial, spectral and structural rich information can only be fully worked in an object oriented environment. This new paradigm of classification, attempts to improve the process of information extraction in environments where the shape, colour and neighbourhood relations are the basis for the correct identification of classes, as in urban areas.

Altimetric data, along with the optical data, are other information source also very useful for urban mapping. Such data can be Digital Terrain Models (DTM) that describe the terrain relief, or Digital Surface Models (DSM) that represent the elevations of the reflective surfaces of trees, buildings, and other features elevated above the terrain. Such topographic models can be used to retrieve the height of the elements above the ground, thought the calculation of a normalized DSM (nDSM), generated by subtracting a DTM from a DSM.

3.8.2 METHODOLOGIES FOR URBAN MAPPING

We conclude that the most appropriate methodology for the large-scale projects shall follow these steps:

- Explain the mapping objectives and characterizing the study area;
- Set a scale appropriate to the objectives to be detected;
- Select a classification system that describes with objectivity the classes of land use in focus;
- Using VHR images and/or altimetric data;
- Data pre-processing, including orthorectification and image fusion;
- Extract the information based on a feature and/or object-oriented approach;

– Assess the quality of the map produced by the calculation of thematic and positional accuracy indices;

3.8.3 METHODOLOGIES TO UPDATE URBAN MAPS

Before implementing change detection analysis, the following conditions must be satisfied (Lu et al., 2004): (1) precise registration of multi-temporal images; (2) precise radiometric and atmospheric calibration or normalization between multi-temporal images; (3) similar phenological states between multi-temporal images; and (4) selection of the same spatial and spectral resolution images if possible. When selecting the appropriate change detection techniques, the determination of change direction is also an important factor. In fact, some techniques, like image differencing, only allow for change/non-change information, while other techniques like post classification comparison can also provide a complete matrix of change directions (Lu et al., 2004). Furthermore, the use of vegetation indices can be advantage since they are more strongly related to changes in the scene than the responses of single bands.

4. EXTRACTING INFORMATION FROM VHR IMAGERY – STATE OF THE ART

The availability of commercial VHR images now provides more detail on the Earth surface than the currently available Landsat or SPOT images. The scientific community has developed numerous applications based on these refined images, using different methodologies and techniques for extracting thematic information.

The development of object-based classifiers, as an alternative to pixel-based ones, started in the 1970-80s with the development of segmentation techniques (Kettig and Landgrebe, 1976; Haralick and Shapiro, 1985, Cortez et al., 1995, Wang and Terman, 1997). These techniques were developed for machine vision (pattern analysis, delineation of discontinuities on materials or artificial surfaces) and quality control, but rarely applied to EO images (Blaschke et al., 2005). Indeed, in remote sensing the attentions were concentrated in image discretization to generate spectrally homogeneous segments. Only later, with the launch of the first commercial VHR satellite (IKONOS) in 1999, did this concept become applicable in remote sensing (Meinel and Neubert, 2004). Consequently, the most relevant studies based on object-based approaches only started to appear in the literature by 2001.

The studies presented hereafter exemplify approaches developed with eCognition and Feature Analyst software. These packages analyze both the spectral and spatial/contextual properties of pixels and use a segmentation process and iterative learning algorithm to achieve a semi-automatic classification procedure, which promises to be more effective and more accurate than traditional pixel based methods. Note that eCognition and Feature Analyst only perform object-based analysis, so all the image processing operations which are upstream of the classification must be done separately in digital image processing software (e.g., ENVI, PCI or ERDAS).

Background information is presented in three major parts expanding upon concepts underlying the case studies presented in the research chapter (Chapters 6). Urban land cover analysis, urban change detection, and building extraction are the topics of this chapter.

4.1 EXTRACTING LAND INFORMATION IN URBANIZED AREAS

The first studies in GEOBIA can be found in conference proceedings and non-peer review literature. Only later peer-review journals started to publish empirical studies (Blaschke, 2010). An example is the work of Bauer and Steinnocher (2001) in land use mapping in urban environment. The research used IKONOS imagery, and the land use inventory of the City Council of Vienna, with 42 classes. The authors made the assumption that the land use functions could be distinguished based on differences in the spatial distribution and pattern of land cover forms. The pre-processing included the fusion of IKONOS bands. The classification was then held in several stages. Initially, the land cover map was obtained with a Maximum Likelihood classifier, using a mask for the roads. The morphological properties and spatial patterns within the land cover map were analyzed and used in the construction of rules for land use classification, in eCognition. The result was a map with 11 classes of LULC. However, although the authors indicated a high degree of correlation between the mapped classes and the reference inventory, this was not quantified through quantitative indices. The authors reported problems in the classification of classes whose land cover structure and composition were similar, but had different functional characteristics (e.g., residential areas with garden and allotment gardens).

Meinel et al. (2001) used an IKONOS image to map the city of Dresden. In this study, the authors compared a pixel-based classifier with an object-based one to assess the potential of those images for urban area mapping. Pre-processing only included the geometric correction of the image. In the pixel-based approach, the multispectral channels of IKONOS, the Normalized Difference Vegetation Index (NDVI) (Rose et al, 1973), and the second principal component were used for a knowledge-based Decision Tree classification. The object-based approach in eCognition used IKONOS' pansharp and the panchromatic images, along with the NDVI. The images were first segmented in three levels. The subsequent classification used the mean grey levels, formal characteristics, neighborhood relations and relations with higher and lower order segments. Both methods produced maps with the same value of Overall Accuracy - 90%. In a visual comparison it was noted that the "salt-and-pepper" characteristic of the pixel approach did not appear on the object-based map. The object-based approach, which incorporated neighborhood relations and surface shape, made the correct identification of sports fields through an analysis of form and size, and some houses through their adjacency to roads. The pixel-based method, applied to the original data set of 4 m resolution imagery, extracted 11 classes, while the object-based method extracted 13 classes from a pansharp data set with 1 m resolution. Concluding, the object-based map produced a lower proportion of unclassified areas as well as a far more homogeneous product, than the traditional pixel-based approach.

Hofmann presented two studies, in 2001, in mapping urban areas with IKONOS images (Hofmann, 2001a; Hofmann, 2001b). The first study aimed to detect buildings and roads from an orthorectified pansharp IKONOS image and altimetric data (DEM), in Tsukuba, Japan. The segmentation occurred in eCognition at various scales, depending on the type of object to be identified and giving different weight to the DEM. After creating a class-hierarchy, the classification used a system that included fuzzy membership functions, Nearest Neighbor classifier, and/or combination of both methods. The DEM allowed a better discrimination of the classes "Building", "Shadow" and "Forest", but with some omission and commission errors. In order to correct these and improve the classification, other attributes were included in the classification system, like shape and context features. The author concluded that the quality of the segmentation improved with the introduction of the DEM and refer the good results of the classification but did not provide any quantification of the level of quality achieved. The second study presented also by Hofmann aimed to detect informal settlements in Cape Town (Hofmann, 2001b), using eCognition. The study assumed that illegal construction was not differentiated by the spectral information but rather by its shape, texture and spatial context. The pre-processing included the fusion of the IKONOS imagery. Segmentation was performed at four levels of resolution. The classification stage used membership functions based on textural, hierarchical and spectral features, and the Nearest Neighbor classifier. The author concluded that the quality of segmentation increased with the pansharp image by increasing the local contrast between objects. Problems mainly occurred within settlement areas where even a visual inspection could not lead to satisfactory results. There was no quantification of the quality of the produced map.

Shackelford and Davis (2003) tested a classification that combined fuzzy pixel-based logic and object-based approach for classifying IKONOS images over urban areas. Pre-processing included pansharpening the imagery. The classification occurred in two stages. In Phase 1, a pixel-based hierarchical fuzzy classification technique, that used both spectral and spatial information, was implemented to classify individual pixels into 7 classes. When compared with a Maximum Likelihood classifier, the fuzzy classifier was 10 to 25% better. However, all man-made structures were classified as either "Road" or "Building". A segmentation and object-based classification approach were then adopted, in eCognition. To further refine the fuzzy pixel-based classification, an “Impervious Surface” class was added to identify non-road and non-building surfaces. A process for identifying segments as “Building” using neighborhood analysis of “Shadow” segments was also implemented. Using these techniques, the object-based fuzzy logic classifier was able to identify “Building” with an accuracy of 76% and “Impervious Surface”, with 81% of accuracy. The final map contained 5 classes, with an Overall Accuracy of 86%.

Herold et al. (2003a) examined the potential use of GEOBIA methods to extract detailed information of land use from seven IKONOS images, in the coastal area of Santa Barbara, USA. Initially, all images were geometrically and atmospherically corrected. An object-based land cover classification was conducted in eCognition using all multispectral bands. The image classification focused on three land cover classes: “Buildings”, “Green vegetation”, and “Rest”, including roads, parking lots, bare soil, water bodies, and non-photosynthetic vegetation. Additional spatial information such as the length/width ratio to separate buildings (compact quadratic/rectangular) from roads (linear), or a rule based on the minimum area to separate bare soil from roofs, were used in the classification stage. The land cover map reached an Overall Accuracy of 82%. Then, additional information was applied to assess land use. Land use regions were derived from photo-interpretation of aerial photography. Spatial metrics (22) and texture measures (7) (based on the GLCM) were then used to describe the spatial characteristics of land cover within each land use region. The authors pointed out that among these, area coverage, the size and standard deviation (mean patch size and standard deviation) as well as the spatial aggregation of the individual vegetation patches (cohesion), provided most land-use discrimination. Building configuration was best characterized by area coverage, the regularity of the spatial arrangement (Nearest Neighbor metrics), the dominance of one large building structure (largest patch index), and the spatial heterogeneity of the individual building objects (edge density). Contagion, as a measure of the overall spatial heterogeneity of a land-use region, provided another important land-use discriminator. The homogeneity was identified as the most suitable texture measurement that makes an additional contribution to the differentiation of urban land uses. The final land use map obtained an Overall Accuracy of 76%. The authors concluded that the accuracy value was encouraging given the extent of the area examined (300 km^2) and the detail of the classification.

Pinho and Kux (2004) presented a methodology for LULC classification of the intra-urban space, aiming to control land parceling processes, zoning restrictions, land occupation and vegetation cover. The approach was based on object-based analysis of QuickBird images, and applied to a town located in the State of São Paulo, Brazil. In eCognition, the segmentation of the pansharp image produced three hierarchical levels of resolution. The objects' classification was then based on training areas. The authors concluded that the QuickBird images had low spectral resolution and that this hampered the classes' distinction. The alternative to try to overcome this low spectral resolution was to use attributes that described the shapes of objects and/or its relations with neighboring objects. To avoid criteria overlapping when classifying some classes (e.g., class "Asphalt" with class "Aluminum cover" and "Concrete"), hierarchical features were used. Even though the software could allow this type of classification, not all the problems of overlap between classes were resolved. The final map obtained a Kappa value of 86% in its finest level of detail.

Wang et al. (2004a) studied the land use classification in a study area where later was built the Beijing Olympic Games Village. The selected image was a panchromatic band from the SPOT 5 satellite. The image was segmented and the objects were classified into 4 classes ("Built-up area", "Agricultural land", "Road" and "Green land") using rules and a fuzzy supervised classifier, available at eCognition. The final map presented an Overall Accuracy of 87%. However, the authors concluded that although the object-based classification was successful, using only the panchromatic band limited the correct classification of "Roads" and "Bare soil".

Gu et al. (2005) tested a methodology to extract residential areas in Beijing, China, from SPOT 5 and IKONOS images. The extraction started in eCognition with the segmentation of the multispectral bands in two levels. The classification of level 1 segments used features like mean value (e.g., objects belonging to class "roofs" have high mean value), homogeneity (from the GLCM) and a shape index (length/width ratio). Thus, the segments were classified into 5 groups: "Roofs", "Roads", "Bare soil", "Vegetation" and "Water." Level 2 (less detailed) segments were used to describe the density of buildings classified at level 1, e.g., the percentage of segments of the roof type determined whether they belonged to a residential area or not. For the quality analysis, instead of using the multispectral bands, the authors chose pansharp images. Through a confusion matrix analysis, the classification of the SPOT image was found to be better (Producer’s Accuracy for “Residential areas” was 92%) than the IKONOS one (Producer's Accuracy for “Residential areas” was 75%).

Damm et al. (2005) investigated the ability of QuickBird imagery for ecological monitoring. The study was conducted in a railway area in Berlin. The image was pansharp and segmented in eCognition into three levels of resolution. In the classification stage, vegetated areas were separated from the rest, based on spectral information. Vegetated and non-vegetated areas were further classified based on spectral information, shape parameters and the pre-classification of level 3. The final map had 7 classes ("Herbaceous vegetation", "Shrubs and trees," "Vegetation on railroad track", "Open soil," "Railroad tracks," "Impervious surfaces", "Buildings"), and obtained a Kappa value of 81%. However, the authors identified the low spectral resolution (which did not distinguish some buildings from other impervious surfaces) and the image date of capture (since the vegetation was poorly developed at the end of winter, the distinction between trees, shrubs and herbaceous vegetation was difficult) as factors that hampered this study. Nevertheless, the results could be used to analyze thematic issues like: the different states of plant succession, the distinction between different types of impervious surfaces, as well as the recent utilization of railway tracks.

Marchesi et al. (2006) implemented in an area from the Province of Milan, a classification to identify urbanized and non-urbanized areas, using QuickBird imagery. In a pre-processing stage, the images were orthorectified, to enable more precise geometry. Segmentation in eCognition was applied in 3 levels of resolution. The information at level 1 was separated in two classes ("Urban" and "Vegetation"), using a membership function based on the vegetation index NDVI. At level 2, three types of roofs were distinguished through a combination of characteristics such as mean layer values and shape properties. The roads were classified based on vector data, and water bodies based on the low value of reflectance of the blue band. The remaining classes were classified by rules that reflected neighborhood relations. The resulting map showed 10 categories of land with an Overall Accuracy of 83%.

Carleer and Wolff (2006) tested an urban land cover classification in an area located in Ghent, Belgium. The selected spectral data was a QuickBird image. The pre-processing included the imagery orthorectification. The segmentation in eCognition occurred in 6 levels and with different sets of bands. Several features were calculated from the segmented images: 10 spectral features (e.g., NDVI), 16 texture features (e.g., contrast in the panchromatic band) and 7 morphological features (e.g., length). The most relevant features were then selected through visual analysis and by calculating the separability between classes. The selected features were then used in the classification operated with the Nearest Neighbor. Level 1 ("Vegetation", "Non-vegetation" and "Shadow") obtained a Kappa value of 99% in urban areas. Level 2 was well classified, but the three classes of vegetation (Kappa of 70-71%) were not so well identified as the non-vegetation (Kappa of 74-78%). The quality of classification in level 3 ("Buildings" and "Transport") varied widely, as they were in urban or suburban areas: the map had a poor Kappa of 51% in urban area and 71% in the suburban area. The authors presented several explanations for this result: the buildings and the roads were better defined in the suburban area; there was less occlusion of roads by shadows or cars; the shape of the buildings was clearly defined because the houses were surrounded by vegetation and the houses were not adjoining, while they were smaller and adjoining in the urban area. Moreover, in the urban area, some streets were completely hidden by shadow or by the elevation displacement of the buildings along the streets, which was not the case in the suburban area. The authors concluded that in dense urban areas, the segmentation could not correctly extract the objects, and the inclusion of ancillary data or solutions based on shadow interpretation could reduce this problem.

Taubenböck and Roth (2007) and Taubenböck et al. (2010), developed a modular object-based classification methodology for imagery from the sensors IKONOS and QuickBird sensors, in two different urban environments (Istanbul, Turkey, and the planned small town of Wuda, China). The developed methodology was a stepwise procedure. Two modules were developed in eCognition: segmentation and classification. The urban land cover classification included 8 classes: “Houses”, “Streets”, “Grassland”, “Trees/bushes”, “Shadows”, “Water”, “Bare soil”, and “Unclassified”. The segmentation produced a basic segmentation level and an optimization level with a higher scale parameter. The final output of this approach provided a single, improved segmentation level having large segments in homogeneous areas, whereas small-scale structures and heterogeneous regions are represented by distinctively smaller image objects. The classification methodology was a hierarchical elimination of non built-up areas. These two modules were developed for the IKONOS data of Istanbul. Afterwards, it was transferred to a different urban environment (Wuda, China) and a different high resolution sensor (QuickBird). The validation procedure revealed an Overall Accuracy of 85% for the IKONOS data, and 78% for the QuickBird data. The authors concluded that the modular concept allowed different classification for high resolution sensors as well as various urban structures with specific interactive adjustment on the particular features. Later in 2010 (Taubenböck et al.), the methodology was transferred for incipient megacity Hyderabad, India, and QuickBird imagery. The validation of both land-cover classifications shows an overall accuracy of more than 81%.

Su et al. (2008) studied the utility of textural and local spatial statistics for the improvement of object-based classification of a pansharp QuickBird image of Kuala Lumpur, Malaysia. Textural features and the local spatial statistics Moran’s I, were used as additional bands in the in eCognition’s classification process. Three combinations of data were tested: spectral values, spectral values and texture bands, and spectral values and local spatial statistics. After segmentation, the objects were classified, using the Maximum Likelihood algorithm, into 7 classes ("Shrub", "Grass," "Water," "Road", "Buildings", "Vacant land" and "Shadow"). In a quality analysis, the three approaches obtained high values of Kappa (78%, 84% and 87% respectively). The authors concluded that both the texture and local spatial statistic produced better results when classifying land in urban areas. However, its contribution depended not only on the selection of optimal texture features but also on the type of land cover being classified. Moreover, Moran’s I was found to be the most appropriate for all conditions, as it could improve the classification accuracy by up to 7%. Another conclusion relates to the size window, the spatial and textural algorithms and direction. All these factors influence the quality of the classification. Each texture feature had its own optimal window. Texture features over image objects were sensitive to direction. Textures calculated over image objects at a 45º angle did improve the classification accuracy of buildings, as this direction could depict the pattern of buildings in the study area. Similarly, for the local spatial statistical feature, the neighborhood rules also improved the classification result.

Lackner and Conway (2008) explored a GEOBIA approach for land use classification, using land cover information from an IKONOS image of an area located in Ontario, Canada. The first step involved the derivation of 17 land cover classes from the IKONOS pansharp image and multispectral bands along with a NDVI layer, ancillary roads data, and textural, contextual and shape parameters, using eCognition. This land cover map obtained an Overall Accuracy of 73%. The land use map was then obtained in three steps. First, a connection between land cover and land use was made through the definition of land use in terms of the land cover classes they incorporate. Secondly, the study area was segmented into meaningful objects, corresponding to land use boundaries. Third, the objects were classified based on the spatial relations among land cover classes. Finally, two land use maps were derived, one with 6 classes and another with 10 classes, with Overall Accuracies of 90% and 86%, respectively. The authors concluded that roads extracted from the land cover map could be very useful in outlining land use boundaries. Moreover, the concise definition for each use to be translated into rules used in the GEOBIA classification was a crucial step. This was relatively straightforward for classes like “Residential” uses, but classes like “Commercial”, “Institutional” and “Industrial” were more difficult because their land cover components were very similar: all three included large “Box buildings” and “Parking lots”.

Weih and Riggan (2009, 2010) compared a pixel-based approach versus an object-based for LULC classification in Arkansas, USA, using two multispectral SPOT-5 satellite images, leaf-on and leaf-off, merged with a color infrared aerial image. Due to correlation between some of the bands of the merged image, a PCA was used to decrease redundancy in the data. Two maps with 9 classes, that include “Urban”, “Roads”, “Railroads” and other land cover classes, were produced using a pixel-based supervised approach and an object-based classification conducted in Feature Analyst. The parameters used in Feature Analyst were Manhattan algorithm with a 13-pixel width, a resampling value of 4 and a minimum aggregate area of 22 pixels. With the object-based method, the “Barren” class was misclassified as either “Urban” or “Grassland”, while “Clear cut” was confused with “Deciduous” and “Barren”. The Kappa values for the pixel-based and object-based classifications were 61% and 78%, respectively. All three urban classes obtained with the GEOBIA approach, yielded Producer’s and User’s Accuracy superior to 83%.

Miller et al. (2009), using an iterative training technique, classified 111 VHR images using the Feature Analyst software. The images were classified into 12 classes: six impervious classes (“Buildings”, “Cars”, “Parking lots”, “Railroad tracks”, “Roads” and “Sidewalks”), and six pervious ones (“Bare soil”, “Field”, “Forest”, “Lawn”, “Water” and “Tree canopy”). The Bulls’ Eye 2 input representation, with 7 pixels width, and minimum object size of 100 pixels were used for classification. The classification had an Overall Accuracy of 91.7%. The User’s Accuracy was 95.2% for the impervious classes and 88.1% for the pervious classes.

There are also some applications in Portugal of object-based classifications of VHR images in urban context. The following paragraphs describe the relevant work.

Fonseca (2003) used an IKONOS image for mapping the area of Alvalade in Lisbon. The pre-processing included imagery pansharp. The image was then segmented in eCognition into three levels according to scale parameters. For each level, a nomenclature was developed and membership functions were created. Level 1 classification identified different land cover types (e.g., "Trees", "Buildings"), whereas level 2 classification already identified land use classes (e.g., "Hospital", "Residential buildings”). Level 3 classification, on the other hand, acted as an auxiliary map in order to help classify the lower levels. The author used the opportunity to build synthetic bands (as the one obtained by the level 3 segmentation) where the level of intensity associated to each object was the class assigned to its super-object. The classification quality was evaluated in two ways. First, the stability of the classification at level 1 (of greater detail) was investigated through the analysis of differences between the two highest degrees of membership associated with each object. Furthermore, a confusion matrix was produced. In this analysis, the map obtained a Kappa value of 97% and high levels of Producer’s and User’s Accuracy for each class. The author concluded that good results were due to the success of the methodology used, and the fact that the study area was small.

Gonçalves (2003) presented the implementation of object-based classifiers on IKONOS images, in an area of Marinha Grande, Portugal. The pre-processing included the geometric correction of data. For the analysis, a nomenclature based on the CLUSTERS classification (for artificial areas) and CORINE Land Cover (remaining classes) was adopted. Initially, several tests were performed with panchromatic, multispectral and pansharp images but, due to computational limitations, only the multispectral bands were segmented. The segmentation in eCognition occurred in four levels. The knowledge-base used for classification was structured as a hierarchy of classes. The techniques used in the classification were rules development, fuzzy membership functions and mask techniques. From 22 classes present in the study area, only 16 could be identified (10 were urban classes). The 16-class map had an Overall Accuracy of 83% and Kappa of 74%. The problems occurred mainly in two types of classes: 1) the classes of land use that had similar structure and land cover but differ in functional characteristics (e.g., "Financial and commercial areas" and "Utilities and local government”), and 2) in classes for which it was not possible to create image objects well adjusted to the structure of the real objects (e.g., "Roads" and "Network Rail").

Freire et al. (2008) tested the extraction of urban features trough remote sensing analysis. Two distinct study areas, in Lisbon, Portugal, were chosen: the old part of Lisbon downtown and a more sparse area, with different land cover classes, located to the East of the downtown. A pansharp QuickBird image was used. Feature Analyst was then applied in both study areas using different classification systems, training areas and masking techniques. In the downtown study area, the class “Roads” was confused with the class “Buildings with dark roof material”, being reinforced by the presence of shadows. The “Vehicles” class was not identified at all. The best mapped classes were “Water”, “Vegetation” and “Buildings with red tile roof”. In the second study area, the classes “Trees” and “Buildings with red tile roof” were better mapped, while the separation between bare soil and impervious surfaces was not possible.

Santos et al. (2009) presented a study on accuracy assessment of features extracted from QuickBird images of Lisbon, Portugal. The classes were: “Buildings with orange tiles”, “Buildings with other roof materials”, “Roads”, “Trees”, “Bare ground”, “Agriculture”, “Sidewalks”, “Vehicles” and “Grass covered areas”. The feature extraction, using Feature Analyst, was a difficult process due to the complex morphology and spatial heterogeneity of the study area. On a visual inspection, the results that were more interesting corresponded to the classes “Buildings with orange tiles” and “Trees”, while the less interesting were “Vehicles”. Based on a confusion matrix, the thematic classification was evaluated, and the Buildings’ class obtained an Overall Accuracy of 68%.

Synthesis

Each one of the 23 studies included in this review, represent a particular aspect of technological advancements in relation to urban analysis. Some of these papers did not refer important experimental details like parameters' selection or no accuracy assessment was reported by the author(s). Such papers were still included in the review, provided that a minimum set of parameters had been specified and due to the relative youth of GEOBIA.

Bauer and Steinnocher (2001) studied the morphological properties and spatial patterns within the land cover map, using the Structural Mapping and Analyzing System. The result of this analysis was then used in the construction of rules for land use classification. Hofmann (2001a) tested the use of altimetric data during the segmentation stage to separate classes like "Shadow" from "Trees". Shackelford and Davis (2003) tested a classification that combined fuzzy pixel-based logic with an object-based approach for classifying IKONOS images. Herold et al. (2003a) presented a study with a large data set (7 IKONOS images) to map land use. The study was carried out in two phases: first the land cover was obtained and then land use information was extracted through a supervised approach using texture measures and landscape metrics. Damm et al. (2005) investigated the capability of QuickBird imagery for ecological monitoring. Using a masking technique, vegetation areas were separated from non-vegetation ones, which were further classified based on spectral information, shape parameters and the pre-classification of the upper scale level. Carleer and Wolff (2006) tested segmentation with different sets of bands like spectral features, texture features and morphological features. Taubenböck and Roth (2007, 2010) developed a modular object-based classification methodology for IKONOS and QuickBird sensors. The developed methodology was a stepwise procedure of a chronological workflow, based on two modules: segmentation and classification, which were applied on two distinct areas and two different image-sensors, with specific interactive adjustment on the particular features. Su et al. (2008) studied the usefulness of textural and local spatial statistics for the improvement of object-based classification. The textural information and the local spatial statistics Moran's I, were used as additional bands in the classification process. Lackner and Conway (2008) explored an object-based land use classification through a step wise process. Firstly, using IKONOS images, a NDVI layer, auxiliary roads data, and textural, contextual and shape parameters, the land cover map was obtained. The land use map was then obtained in three steps, using the thematic information from the land cover map.

4.2 EXTRACTING CHANGE INFORMATION FROM VHR IMAGES OF URBAN AREAS

In the last three decades many techniques have been developed for change detection in satellite images. The revisions made by Singh (1989), Coppin and Bauer (1996) and Lu et al. (2004) provide a good summary of the existing methodologies. Change detection methods were initial designed to operate in medium and low spatial resolution data (e.g., Lyon et al., 1998; Hayes and Sader, 2001; Seto and Liu, 2003; Chen et al., 2003a). More recently, studies on land cover mapping with images of VHR started to be published. In this type of images, unlike the medium and low resolution ones, the notorious presence of shadows and off-nadir image capture angles, make it more difficult to interpret changes. (Niemeyer and Canty, 2001). In combination with these characteristics, there is a large amount of spectral and spatial information that is of great relevance to describe the richness of elements and structures in urban areas. Consequently, many traditional change detection methods do not have great success with VHR data (Im and Jensen, 2005). Consequently, the detection at the pixel level is being replaced by the detection at the object level (Niemeyer and Canty, 2001; Niemeyer and Canty, 2003; Walter, 2004a).

Carleer and Wolff (2004) divided the techniques for detection of changes in two groups according to the data used: the image-database change detection and the image-image change detection. The applications from the first group make use of existing expert knowledge in the database and avoid radiometric correction, thus the accumulation of errors results from post-classification analysis. The applications from the second group employ the classification methods already described in section 2.3. The following literature review is grouped according to this dichotomy.

4.2.1 Detecting Changes by Comparing Processed Images with Vector Databases

Most digital analyses conducted in urban areas are based on GIS data and satellite imagery. This is probably because traditional change detection methods often have poor results due to the complexity of urban landscapes, and cannot effectively use multi-source data analysis (Lu et al., 2004). The information extracted from the GIS allows knowing where the object is in the image, limiting the area of analysis and the rate of false alarms. Furthermore, it provides knowledge about the existing land cover before the change, allowing development of rules for the most likely change scenarios when analyzing images from later dates.

The studies described in this section are examples of applications where the goal is to identify changes from GIS data and satellite imagery, in order to update the GIS information or to make use of this information when producing new maps.

Tenedório (1998) presented an investigation for detecting land cover changes in the urban fringe through the combination of SPOT HRV imagery and a vector layer with land cover polygons, in a study area located in Paris, France. The aim was to identify those land cover polygons (zones) that changed in the period under analysis. The change detection was based on two satellite images, and the layer with the MOS (*Modes d'Occupation du Sol*) zones. Each zone was spectrally characterized based on a combination of six indexes. For each index, a stability limit was defining according to the land cover class. The final product was a zone affection change map.

Walter (1999; 2000) proposed that the traditional definition of training areas to detect changes, using the manual delineation, be replaced by an automatic approach based on GIS. The goal was to avoid a subjective process that required expert digitization and the need for a new edition whenever the data source change (due to atmospheric effects, different Sun angles, different times of growth, etc.). Assuming that the number of objects modified in the real world is significantly less than the total number of objects represented in the database, the information therein can be used to automatically define areas of training.

In a subsequent study (Walter, 2004a), the author tested this procedure to update a GIS database, at 1:25 000 scale, using an change detection approach based on GEOBIA, in two study areas located in Germany. The data used were the cartographic and topographic national database (Amtliches Topographisch-Kartographisches Informationssystem - ATKIS) and digital images captured by aircraft, with 2 m spatial resolution and 4 bands (visible and near infrared). The ATKIS contains 63 classes of objects, but given the difficulty in identifying some uses with a pixel of 2 m, the author chose to group all the objects into 5 classes: "Water", "Forest", "Urban area", "Green areas", and "Roads". The object-based classification used 16 layers: spectral bands, texture images, and percentage of pixels correctly classified as “Forest”, “Greenland”, “Settlement” and “Water”, on a pixel based approach. The two study areas contained a total of 951 objects, all used as training areas, meaning that among these are also training objects that are wrong in the database. Altogether, 82 objects (8.6% of all objects) were classified into a different land-use class than the one assigned to them in the GIS database. From these 82 objects, 45% were real changes, 31% were potential changes, and 23% were wrongly classified. The author concluded that other data sources should be further explored: radar images (to better separate residential areas from industrial areas), other texture measures, and multi-temporal data.

In a later work, Walter (2004b) applied the previous methodology, plus a LiDAR image, to improve the separation between residential and industrial areas. The first step was the pixel-based supervised classification, using 4 spectral bands, LiDAR image and texture measures. The resulting map was then used as a band in the object-based classification. Both classifications were based on the Maximum Likelihood classifier, and the training areas were drawn from the GIS database. The characteristics used to distinguish residential from industrial areas in the object-based classification, were the average size of buildings (residential buildings are generally smaller than industrial buildings), their average roof slope (residences have sloped roofs), percentage of trees (greater in residential areas), percentage of sealed ground (higher in industrial areas) and textural appearance (more homogeneous in industrial areas). The methodology was applied in an area with 190 residential buildings and 84 industrial buildings, located in Germany, and on the same database used in Walter (2004a), plus the LiDAR image. The resulting map identified three classes of objects: "Ok" (236 objects), "Not Ok" (3), and "Unclear" (37). However, one can see that due to the automatic collection of training areas, the methodology was based on the geometry of objects as described in the GIS database, compromising the identification of minor changes. Indeed, if a building appears in a large forest area, the proposed method fails to identify it.

Bailloeul et al. (2003) proposed two methods for updating an urban GIS database using QuickBird images of Beijing, China. Both methods were based on information from the GIS and a DSM. The first method used GIS data and only one image. The main goal of this approach was to detect changes between outdated GIS data and a recent satellite image using *a priori* knowledge and deformable models. The change detection was made with deformable models which act on GIS objects and adapt them to the objects of the image. If the adjustment was successful, then it was assumed that there was no change there. The “Changed” and “Not changed” objects with greater confidence were then used to update the GIS. The second method used two images and GIS data. The first image was contemporaneous with the GIS and represented the original information. Segmentation by region growing was performed on both images for change detection. Each GIS object identified a seed that initiates a region growing process at the same location of the sensed scene in the two images. The comparison of the segmented regions in both images allowed to measure change. Areas of no change defined the training areas for the classification of the later image. Objects extracted from changed areas were vectorized and entered into the GIS database. Comparing the two methods, the authors pointed out the limitation of the 1st methodology, in which the detection was based on the objects’ border, making any object semantically different but with the same limits, not detectable. However, this problem arises only for elements at the ground since the DSM can outwit the other cases. Both methods were very sensitive to the image-GIS registration.

Wang et al. (2006) used a QuickBird image to update a cadastral GIS, of 1:2 000 scale, from a suburban area of Shanghai, China. The classification started with watershed transformation segmentation. The feature extraction used the spectral images and the NDVI, the texture measures and geometric indices (area, compactness, elongation, etc.). First, a set of rules based on training areas for each class, were built. The vegetation was then removed using the NDVI. The fallow crop lands were classified using panchromatic values and texture information. The water was separated from the asphalt roof using the NDVI and geometric features. The remaining objects were labeled as "Unclassified". Next, a rule-based system was set up to judge, for every parcel, whether or not change happened comparing to the existing GIS. Small objects were removed from the comparison because they were subject to registration errors, among others. The rules for change detection were based on the percentage of each land cover class within the corresponding portion of the GIS (e.g., if the attribute is residential and the percentage of sealed exceeds 0.7, then the object remained unchanged). The authors concluded that the methodology had greatly reduced the manual classification effort, but improvements could be achieved with additional data such as radar images.

Frauman and Wolf (2005) tested four methods to update the Belgian topographic database, at 1:1 000 scale, with IKONOS and QuickBird orthorectified imagery. The methodologies tested were supervised multi-temporal classification, unsupervised multi-temporal classification, post-classification change detection and detection based on GIS. The fastest method to detect changes was multi-temporal color composite, however, no information beyond the visual identification is given. The unsupervised method was quickly implemented but could not distinguish many classes and also required visual interpretation. The supervised method yielded more information on the change directions than the previous one. The post-classification method was more complex to implement but also more precise about the types of change that occurred. The GIS-based technique showed a great potential because it focus the detection in the areas of interest. This technique also drew attention to errors in the database. For example, a vegetation area that had been attributed to “Buildings” objects and that had not changed would not appear as a changed polygon on the classifications but would appear as “Vegetation” within the “Buildings” mask, signaling a mistake.

Bouziani et al. (2007) proposed an GEOBIA methodology to detect changes in buildings, using VHR images, cartographic data and *a priori* knowledge. The data included an IKONOS image, from the city of Sherbrooke, Canada, and the topographic database of Quebec, at 1:20 000 scale. The second area of study was located in the city of Rabat, Morocco, and included a QuickBird image and a 1:10 000 topographic base. The methodology applied in these two study areas was developed in six steps. The first step involved modeling the knowledge base. Five classes were taken into account: “Buildings”, “Roads and parking lots”, “Vegetation”, “Water”, and “Shadow”. A set of characteristic features were collected for each class and included in the knowledge base (e.g., the area feature to separate individual buildings from parking lots), as well as rules for the possible transitions (e.g., roads do not change to buildings). The second step was the region growing segmentation of the image, where the seeds were the centroid of the objects in the GIS. After segmentation, various attributes were calculated for each segment and a contextual analysis was applied (e.g., segments adjacent to the potential shadow segments in the direction of the Sun azimuth angle are potential buildings). The fifth step was the object features learning, where the training areas were located using the database. Then, for every object of the existing geographic database, corresponding segment (or segments) of the image were identified. Once the segment was found, its spectral, geometric and contextual features were generated and saved in the knowledge base. The outcome of learning was then used to interpret the image. At this stage, the minimum distance between buildings and streets, for example, was calculated from the GIS data, and stored in the knowledge base. This distance was then used to detect new buildings. The last phase was the definition of rules for identifying changes. The authors applied four kinds of rules: spectral, geometric, contextual and transition rules. These rules had an associated degree of confidence and helped dealing with the imprecision of the data and the vagueness of the rules themselves. An accuracy assessment indicated a rate of correct buildings detection of 70% for Sherbrooke, and 90% for Rabat. Regarding the geometric accuracy, the average error for the IKONOS image was 3 m, and 2 m for QuickBird. In conclusion, the authors pointed out difficulties in the correct delineation of the new buildings: 20% of the new buildings were detected with a surface rate (rate between the surface of detected building and the actual surface of this building) lower than 80%.

Hanson and Wolf (2010) compared built-up and roads extracted with a hierarchical region-based classification method (eCognition), to the ones of an old geographic database in order to detect changes. A simulation of PLEIADES data from Toulouse, France, with a resolution of 0.7m in the panchromatic band and 2.8m in the multispectral bands, was used together with a DSM derived from SAR Cosmo-Skymet data. The topographic database was generalized in 5 classes, and its outline was used as a first level during the segmentation process. The authors conclude that the use of a DSM in the classification stage resulted in better change detection accuracy. When evaluating the change detection, the quality increased from 75 to 78% with this introduction. Regarding the nature of the change, the quality went from 73%, without DSM, to 74%, with the DSM. Nevertheless, the DSM contribution was limited by its low resolution (5 m).

4.2.2 Detecting Changes in Multi-Temporal Images

The approaches to detect changes using only satellite images are based on the assessment of different image-dates. Here the level of analysis can vary: pixel, primitives extracted from images, or objects. The following studies make use of one or more of these levels of analysis.

Niemeyer and Canty (2003) studied the detection of changes in two IKONOS images, to monitor nuclear facilities in the province of Ontario, Canada. Firstly, a pixel-based changed detection analysis by Multivariate Alteration Detection (MAD) (Nielsen et al., 1998) was applied. This method produces change components, by selecting a threshold, to distinguish the changed from no-changed areas. Many changes were false because the images were captured with different Sun angles. To improve these results, the authors tested a GEOBIA approach. The data used were the four change component images calculated by MAD and the panchromatic and multispectral bands from the latest image. The IKONOS image was segmented at different scales and four classes of change were defined: increase and decrease in brightness, increase and decrease of vegetation. A class for water areas was also added to the set of classes. The membership functions were established according to the standard deviation of the MAD components, some mean object values, and object relationships.

Vijayaraj et al. (2005) developed a methodology for detection of changes using an object and feature space fusion approach on two orthorectified QuickBird images of the city of Starkville, Mississippi (USA). Change detection was performed using raw multispectral and pansharp image data, and results were compared. The aim was to extract information of new urbanizations and new water bodies. The proposed methodology used the segmentation of the later image to find changes in the original image. In a first step, the images were radiometric normalized for proper comparison, followed by the segmentation of the later image (multispectral bands and bands from Intensity-Hue-Saturation processing). The objects' boundaries were used to analyze their situation in the earlier image. The objects that changed were classified using information provided by water and vegetation indices and the difference image of the Hue bands in the two dates. Thus, the new urbanizations and water bodies were classified and a basic land cover map of the unchanged features was produced. The final map returned 7 land cover classes: "Cleared", "New urban", "New water bodies", "Shadow", "Urban", "Vegetation", and "Water bodies". By visually comparing both results (from original bands and from a pansharp image), the authors concluded that the pansharp image identified the objects with greater accuracy.

Im et al. (2007a) studied an object-based change detection based on correlation image analysis segmentation. Two QuickBird images, radiometrically normalized, from two study areas located in Las Vegas, were used in this test. One of the areas was residential and the other a golf course under construction. The correlation image analysis was based on the fact that pairs of brightness values from the same geographic area (e.g., an object) between two image data sets from different dates tend to be highly correlated when little change occurred, and uncorrelated when change occurs. The authors investigated five methods: 1) the object-based detection incorporating object correlation images (OCIs), 2) object based change classification incorporating neighborhood correlation images (NCIs), 3) object-based change classification without contextual features, 4) per-pixel change classification incorporating NCIs, and 5) traditional per-pixel change classification using only bi-temporal image data. Five non-change classes and three classes of change were defined. The change classification using the bi-temporal image data sets plus the OCIs based on Decision Tree logic, rated the highest classification accuracy with a Kappa of 89%. The object-based change detection presented several limitations. In this study the object's (polygon) geometric problems were removed by analyzing the composite imagery, and not each imagery date. However, errors caused by the different view angles of the multi-temporal image data sets were still present in the composite imagery and were accumulated through the subsequent analyses.

Zhou et al. (2008) developed a GEOBIA approach for land cover classification and change analysis in the Baltimore metropolitan area (USA) using multi-temporal imagery. The data included VHR digital aerial images (pixel of 0.6 m), a LiDAR image and other auxiliary vector data. The images were obtained for two dates (1999 and 2004). The vector data (property parcel boundaries and building footprints) were used to segment the images. The classification phase focused on all the spectral bands, elevation information and the auxiliary information. The object-based classification of the images was performed separately on the two dates and 5 classes were used: "Buildings", "Pavement", "Trees and shrubs", "Herbaceous vegetation and grass", and "Bare soil". The Kappa value of the maps from 1999 and 2004 was 90%, and 92%, respectively. After the classification, a comparison of two change techniques was done: post-classification at the pixel level vs. object level. In this evaluation, 16 classes were tested (15 change and 1 no change). The pixel-based post-classification change detection began by first generating a difference map between 1999 and 2004, subjected then to a smoothing algorithm to reduce the “salt and pepper” effects and remove the edge errors caused by spatial inaccuracies between dates. Regarding the object-based change algorithm, the first step was using both land cover classification maps (1999 and 2004) as thematic maps in the segmentation. After segmentation, a knowledge base of change detection rules was created in order to classify the imagery into 16 change classes. In order to reduce the edge errors due to misregistration, objects classified as possible change were reclassified as no-change, if their widths were less than 3 m. The same happened to those objects with areas smaller than 10 m^2 to reduce the ″salt-and-pepper” effect. Then, the objects corresponding to possible changes were classified into 5 classes: "To building", "To pavement", "To trees and bushes", "To herbaceous vegetation and grass", and "To bare soil”, according to the information of the 2004 map. Rules varying by land cover type were then created to either further classify those objects into sub-categories or eliminate false detection errors. The two change maps were then compared. The pixel-based map had a Kappa of 71%, while the object-based map had a Kappa of 82%. The authors confirm that GEOBIA methods are less sensitive to misregistration’s undesired effects. In most of the cases, both the user’s and producer’s accuracies of the individual classes were significantly improved in the object-based map. In particular, the commission errors for most of the classes have been greatly reduced.

Yuan (2008) evaluated the land cover change dynamics and their effects for the Greater Mankato Area of Minnesota (USA) using image classification and GIS. Four land-cover classes – “Impervious surface”, “Forest”, “Cropland/grass”, and “Water” – were defined. Feature Analyst was used for the classification of two data sets, a black and white aerial photo from 1971, a color air photo and a QuickBird image from 2003. A texture image was stacked with the original aerial photo as an additional layer for land-cover extraction in the earlier date (1971). For the 2003 image classification, color aerial photography and a QuickBird pansharp image were used, minimizing shadow problems. Error matrices were completed based on visually-labeled samples to assess the accuracies of classifications. The Kappa statistics were 87% and 90%, respectively, for 1971 and 2003.

SYNTHESIS

Two general change detections approaches were found in the literature: using GIS data along with EO images or multi-temporal data analysis. The work of Walter (1999, 2000 and 2004b) was based on information available in GIS databases. Using already mapped land objects, the change detection is conceptually simpler. If this information exists in the pre-change situation, and assuming that change only occurs on a minor part of the area under analysis, its geometry and thematic label can be used to train supervised classifiers or build transition rules. This procedure allows reproducing the land cover pattern or implementing rules that reduce false detection, in the subsequent image-dates. However, the approach requires very precise registration between the GIS database and the imagery. Furthermore, the changes are limited by the initial geometry of the objects (changes, smaller than the minimum mapping unit, are compromised). In a similar approach, Bailloeul et al. (2003), used information stored in a GIS as a pre-change representation of the object's geometry. Instead of using it as training areas, the initial geometry was compared with the later geometry through deformable models, to search for similarities. Another approach is using the database in an image segmentation process, where the initial polygons set up the seeds for new regions. Wang et al. (2006) also used GIS data to create rules to reclassify a map produced from a latter image. Bouziani et al. (2007) applied these three approaches for map updating: GIS geometry used for training classifiers, to segment images, and to construct change rules in the same change detection procedure. Frauman and Wolf (2006) reported another benefit of using GIS data in change detection. In their study, the topographic map being updated could be improved due to errors detected when applying change detection rules using thematic information available in latter images.

From this review, we conclude that information in a GIS database can be very useful for change detection. First, it reduces the image area to be analyzed, thus reducing the calculation time and the rate of errors. On the other hand, GIS data can be used for training areas for supervised classification, automating a process that usually requires a large manual effort. Finally, the GIS data can be used to enrich the knowledge base with specific information that can be used for defining change rules. As for the spectral data, these may include one or two images. In the latter case, the image coincides with the oldest date GIS data and represents the pre-change situation. In this review two aspects are pointed out: 1) matching the size of training areas only to the dimension of polygons in the GIS may prevent the detection of changes in smaller areas, and 2) the quality of the imagery-GIS data registration, is a vital step to the success of a methodology based on multi-temporal analysis.

Another approach for change detection based on VHR imagery is using multi-temporal image analysis. In many areas there is still great demand for localized digital data, thus image analysis serve as surrogate data representative of LULC features, allowing mapping when it is not possible to conduct direct measurement of the landscape. Niemeyer and Canty (2003) compared a pixel-based change classification with an object-based one and concluded that the later classification achieves higher quality. Vijayaraj et al. (2005) used the segmentation of a later image to find changes in an earlier image. Im et al. (2007a) applied image correlation analysis to two land cover maps obtained through object-based classification. Zhou et al. (2008) used vector data to segment an imagery data set in a post-classification comparison. Pixel-based and object-based post-classifications were evaluated and the object method rated higher.

After this review we can conclude that multi-temporal analysis is usually conducted separately in each image and the change detection takes place in a post-classification comparison. An alternative is the classification of all image dates as a unique data set. The work of Im et al. (2007a) is an example of such an application. While the post-classification comparisons suffer from problems due to differences in object geometry between dates, the classification of a unique data set overcomes this problem. However, errors due to different image capture angles or Sun illumination conditions continue to be present. Thus, the accurate registration of the images plays a key role in the classification success, as well as the similarity of the solar conditions when acquiring the images.

4.3 EXTRACTING BUILDINGS USING ALTIMETRIC AND SPECTRAL DATA

The primary sources for urban characterization are spatial and statistical data. The latter include socio-economic and demographic information that can be obtained via census or surveys on people and/or companies. Spatial data describe, on the other hand, the physical structures that cover the surface, like buildings, green spaces or roads. Such data can be obtained through optical and altimetric data, along with cartographic information (e.g., urban plans, LULC maps).

Extracting buildings from satellite imagery is a well documented research area in the remote sensing community (e.g., Hofmann, 2001b; Lee et al., 2003; Kim et al., 2004; Dutta and Serker, 2005; Herold et al., 2005b; Liu et al., 2005; Lefèvre et al., 2007; Lackner and Coway, 2008). In addition to the optical images, the inclusion of altimetric data can result in a more accurate extraction (e.g., Hofmann, 2001a; Vögtle and Steinle, 2003; Centeno and Miqueles, 2004; Doxani and Stamou, 2004; Mayunga et al., 2007; Zhou and Troy, 2008; Vu et al., 2009).

Elevation data can be obtained from direct land surveying data or, more commonly, by remote sensing techniques. These include photogrammetrically derived measurements from stereo images, LiDAR point clouds, and IfSAR (Interferometric Synthetic Aperture Radar) active microwave measurements. When comparing these three methods, the following differences arise:

- IfSAR is the only method that does not generate elevation data with vertical accuracy less than 1 meter;
- Airborne LiDAR has become an accurate, cost-effective alternative to conventional technologies for the creation of altimetric data at vertical accuracies that range from 0.15 to 1 m (Hill et al., 2000);
- When comparing building extraction from IfSAR and LiDAR data, Gamba and Houshmand (2000) showed that LiDAR data provided a better shape characterization of buildings;
- LiDAR has two major advantages over photogrammetric systems: (1) the acquisition of vertical information over a large area is cost-effective; and (2) there are fewer requirements for data pre-processing (Meng et al., 2009a).

The combination of data over urban sites, acquired from different sensors, potentially allows for a better feature extraction. In one hand, VHR images provide accurate detailed texture and color information, useful for extracting urban features. On the other hand, LiDAR data are dense 3D sample points of building and terrain surfaces. Furthermore, one single sensor technology seems incapable of capturing detailed and varying characteristics of building models. Consequently, fusing these complementary data sources seems a good option to produce more accurate automatic urban models. This assumption was confirmed by the work developed under the EuroSDRproject which compared accuracies obtained with photogrammetry and laser scanning in building extraction. Kaartinen et al. (2005) confirmed that laser scanning is superior in deriving building heights, extracting planar roof faces and ridges of the roof, whereas photogrammetry and aerial images are superior in building outline and length determination.

The following paragraphs are a review of methodologies for building extraction using spectral and altimetric data, namely LiDAR data, presented in the scientific literature.

Haala and Brenner (1999) tested the use of LiDAR for building and tree extraction in urban environments, using two approaches. The first method combined multispectral imagery (0.3 m resolution) and an nDSM. The nDSM was integrated, along with the spectral data, in an ISODATA classification. The result of the unsupervised classifier was a map with "Shadow", "Building", "Tree", "Grass-covered-area" and "Street". The second method used laser data and 2D ground plan information to retrieve a 3D reconstruction of the buildings. The integration of laser data proved successful.

Hofmann (2001a) used an object-based classification scheme to detect buildings and roads in IKONOS data using a DSM derived from elevation points collected by an airborne laser scanning overflight. The DSM was used for the initial segmentation and for the subsequent object classification in eCognition. The DSM allowed describing the differences in elevation between neighboring objects during classification (e.g., Buildings and shadows were better detected by their relative height differences between neighboring objects). Furthermore, the use standard deviation of the DSM values allowed discriminated flat areas and "variably surfaced" areas (e.g. settlement areas, forests vs. fields and meadows). With respect to the roads classification, they were hardly detectable considering their spectral and elevation properties only. Since they are typically long and narrow, shape criteria are better suited to describe them. The author concluded that, in cases of large and tall objects such as large buildings, the DSM helped improve the shape generation and subsequent classification.

Rottensteiner et al. (2003) integrated LiDAR and multispectral data (0.15 m resolution) for the detection of buildings and roof segments. A first return DSM and a last return DSM were derived and sampled into a 1 m grid. From the optical data, a NDVI image was also computed. These data sets were then used to assess initial building regions, based on thresholding of cues (e.g., large height differences between first and last return data, or high NDVI indicated areas covered by vegetation, that were erased from the building mask). The initial candidates were improved by evaluating their surface roughness and average NDVI, in order to obtain the final building regions.

Vozikis (2004) derived a Digital City Model through image and LiDAR exploration. The first step comprised the search for potential building areas in the images, by looking for radiometrically homogenous regions that exceed a certain elevation threshold. Once the location of a potential building was found, the next step was to extract its geometric properties (building corners) using an adaptive region-growing algorithm for marking the building outline. Afterwards a step-by-step Hough transformation was employed in order to gather the required edge and corner information. To each building one height value was assigned, hence horizontal roofs were assumed. The final step was the comparison of the old state of urban areas (in form of a digital cadastre map or a GIS) with the newly derived Digital City Model representing the current state. In this comparison new buildings were detected, changes in buildings were recognized, as well as areas where old buildings were demolished.

Vögtle et al. (2005) used airborne laser scanning data to automatically select suitable areas for the installation of solar panels. The extraction of the roof planes was based on the DSM derived from the point cloud, using a specific region growing algorithm. Initially, the roof planes were extracted for the whole data set. By using building footprints, the information about the planes and their sizes were assigned to individual buildings. The selection of suitable roofs was done within a GIS database management system.

Walter (2005), evaluate change detection in urban areas, using already existing data from GIS as prior information and combining image data from different sources (multispectral and LiDAR data, both with 1 m resolution). The approach consisted of two classification steps. In a first step, a pixel-based classification was performed, and its result, as well as the input channels (the multispectral and LiDAR data), were then used as an input for the object-based classification. Each object was described by a 5-dimensional feature vector to decide if a settlement object represented a residential or an industrial area (average size of houses, average roof slope of houses, percentage of trees, textural appearance and percentage of sealed ground). Very often only three or four characteristics were valid for a specific object, but this was not problematic because the object-based classification classified the object to the most likely class, through a Maximum Likelihood classification.

Carneiro et al. (2008) implemented a 2.5D urban surface model from LiDAR data, in a study area located in Geneva, Switzerland. Three data sources were used: raw LiDAR data, 2D digital maps of buildings footprints and alphanumerical data containing altimetric information about buildings heights. First, a DTM was produced by classifying the LiDAR points. Secondly, a value was interpolated (using only the LiDAR points contained within the vector building footprints) for each grid cell corresponding to a roof value contained within the area defined by building façades, for all the existing buildings in the study area. For each building, and more specifically for each grid cell contained within, the building height was taken to be the value obtained by subtracting the terrain elevation (calculated in the interpolated DTM) from the building elevation. Lastly, each building was added to the DTM as a column (whose borders are defined from the vector building footprints), using the building height determined previously for each cell contained within. The final result allows the construction of a 2.5D urban surface model, which was composed of only terrain and building height information (DTM + nDSM). The process allowed refining vertical surfaces of buildings and to process façades and roofs separately.

Kassner et al. (2008) used building outlines, obtained by stereo-photogrammetry of aerial photographs, to mask roof contours within a LiDAR point cloud. The remaining LiDAR data, which represented the buildings' roofs, were interpolated into a raster. Afterwards, the roofs were analyzed according to aspect, slope and shaded areas which, according to the prevailing percentage of classified area, allowed a distinction of flat and sloped roofs. Due to the presence of misplaced DSM points, modeling buildings' outer borders and precise delimitation of different inner roof segments was problematic. Furthermore, areas along roof borders and roof ridges also caused problems.

Rutzinger et al. (2008) tested a raster and point cloud based approach for building detection. This analysis was conducted in two phases. The first one was the raster-based object derivation in 2.5D. The second one was a point-based object derivation using the planimetrically defined objects to derive 3D objects in higher detail. The 2.5D model was achieved by segmentation based on a fill sinks algorithm applied to the inverted DSM, followed by a rule-based classification. The 340 buildings of the test site could be extracted with 85% User's Accuracy and 92% Producer's Accuracy. The subsequent roof facet delineation was performed in the point cloud to provide the highest accuracy. In this step, each building was subjected to a 3D segmentation searching for planar roof patches.

Demir et al. (2008) tested four different approaches to exploit the information contained in a multispectral image (0.125 m resolution) and LiDAR data, for extracting different classes of objects and buildings. The first method was based on nDSM (2 m resolution) in combination with NDVI analysis for building extraction: by applying thresholds to both nDSM and NDVI, trees were extracted and these were subtracted from the nDSM, to yield the buildings. The second approach was a supervised multispectral classification refined with height information from the nDSM. The third method used voids in the DTM and the NDVI classification. The last method was based on the analysis of the vertical density of the raw DSM data, generally much higher at trees than at open terrain or buildings. The accuracy of the building extraction process was evaluated through comparison with reference data. The method based only on LiDAR data, performed best in terms of correctness (92%), but is the worst in terms of completeness. On the other hand, the method based on LiDAR and NDVI data, extracted the majority of buildings but other objects were also included, resulting in the worst correctness value (76%). With the union of the four building detection results, the omission rate decreased (8%) but also correctness (81%), while the intersection of all results gave the best correctness (96%).

Jochem et al. (2009) detected roof planes in a LiDAR point cloud. Initially, terrain points were separated from object points using a DTM. Then, through thresholding, low objects like small vegetation, cars or fences were eliminated. This was accomplished by selecting for the classification and segmentation process those points having a height more than 2 m above the terrain. Afterwards roof planes were identified, as a result of a region growing process where all points covering roof planes were detected, classified by roughness and segmented into homogeneous areas of similar normal vectors. A high percentage of detected roof facets including vegetation could be corrected by adjusting the parameters of the segmentation process. Another problem occurred with edges within the selected area. Due to their density and height above ground (i.e., > 2 m) they were also recognized as planar patches and could hardly be removed by adjusting settings. Orthophoto comparison was used for error assessment, resulting in 94% completeness and 88% correctness.

Vozikis (2009) compared different methods for automated building extraction from aerial and spaceborne imagery, including QuickBrid and IKONOS images. The first step was the production of the nDSM. Then, approaches employing the Hough Transformation (that extracts building edges and corners), pattern recognition procedures (image matching by correlation) and texture analysis were examined. Through a quantitative analysis, the approaches were evaluated concerning the completeness of building detection. The method that produced better results over low urban areas was the one based on the Hough Transformation (97% of correctly found buildings). A qualitative analysis, based on a comparison between the building outlines derived by using the proposed automated methodology, and manually mapped buildings (image restitution) was also performed. The residuals of each building corner from the manual mapping, and the closest point of the automatically extracted shape, were computed as a quality measure. From this analysis, the texture analysis rated a higher RMSE (1.379 pixels). Through the research based on adaptive region growing and on the iterative Hough Transformation, the author concluded that the method had some weaknesses. One is the strong dependence on the radiometric quality of the input imagery. Furthermore, very small buildings were not treated correctly. Image matching proved to be a very effective, but very time consuming method. The texture analysis, although very efficient for pattern recognition over areas in small scale imagery, was not very successful for extracting individual buildings.

Khoshelham et al. (2009) presented a comparative analysis of different approaches for automated building detection using aerial images and laser data at different spatial resolutions. Five methods were tested in two study areas using features extracted at pixel and object level, keeping the same training set for all methods. The methods include nDSM thresholding, Bayesian methods (Minimum Distance and Maximum Likelihood), Dempster-Shafer method (similar to the Bayesian approach, but where the hypotheses include not only all classes but also any union of the classes) and the Adaboost algorithm (a method of combining classifiers that are iteratively created from weighted versions of the learning samples). All methods worked with three features: the height difference between the last return DSM and the DTM, the height difference between the first and the last return DSM, and the NDVI. The two study areas differed in the data resolutions: nDSM with 1 and 0.5 m, and images with 0.5 e 0.25 m. The methods' evaluation was based on error measures obtained by comparison with a manually generated reference map. Dempster-Shafer method had the best performance (Overall Accuracy of 97%), followed by the AdaBoost algorithm in both study areas, although these two methods also yield a number of unclassified pixels. The method of thresholding the nDSM performed well in terms of the detection rate and reliability in the less vegetated study area, but also yielded a high rate of false positive errors. The Bayesian methods performed better in the study area where buildings had similar heights. In both study areas, most of the errors were found at building boundaries and in areas where dense trees were present.

Chen et al. (2009) combined QuickBird imagery and LiDAR data, to extract nine types of land cover objects over urban areas. The hierarchical information extraction process was applied in three steps: black body ("Water" and "Shadow") extraction using the Spectral Shape Index, vegetation ("Shrub" and "Grassland") extraction using the NDVI, and non-vegetation ("High building", "Low building", "Crossroad", "Road", and "Vacant land") extraction using the nDSM (1 m resolution). Image segmentation was necessary in every step to obtain image objects. Height differences, length/width ratio and asymmetry allowed the extraction of "Buildings", "High crossroads", "Roads" and "Vacant land". The classification accuracy of these land cover types was high: the Producer's Accuracies of "High building", "Crossroad", "Low building", "Road", and "Vacant land" were 93%, 100%, 93%, 86%, and 66%, respectively. The comparison of the classification accuracy between this method and the traditional pixel-based method indicated an improvement from 69% to 89%.

Ali et al. (2009) compared the results of a pixel and object-level fusion of a LiDAR derived nDSM (1 m resolution) with color aerial photography (0.5 m resolution) and multispectral imagery (0.5 m resolution), based on reference information collected through field survey. Pixel-level fusion of the color photography and the nDSM produced better results than simple classification of color photography. The same result was obtained for the multispectral imagery and the nDSM. Object-level fusion achieved superior results compared to all pixel-level classifications. Object-level fusion of the color photography and the nDSM had the highest classification accuracy (91%), while the multispectral imagery and the nDSM achieved 90% of accuracy.

Santos et al. (2010a) evaluated the contribution of elevation data in the quality of extracted buildings, in a study area located in the city of Lisbon, Portugal. Two maps were produced and compared. One map was obtained by classification based only on spectral data (QuickBird image) while the other map was obtained using spectral and altimetric data (a second return nDSM). The same extraction methodology was applied in both scenarios, using the same training features. To evaluate the quality of the two maps, a comparison with a cartographic layer was carried out. The best extraction results were obtained for the feature class “Buildings”, mainly due to the inclusion of altimetric data. The gain in quality was 12%, from 60 to 72%. However, features like building annexes or multi-family buildings with varying roof covers or elevator shaft in the same building, as well as the presence of different residential typologies, made the feature extraction more difficult and complex. The fact that the image had an off-Nadir angle of 12.2º, and the LiDAR data had an orthogonal acquisition, made the referencing for taller buildings less accurate than for single-family houses. This situation also contributed to the Omission Error of 25%.

Dinis et al. (2010) presented a study in an area located in the city of Lisbon (Portugal), which combined a multi-temporal data set of high resolution satellite imagery and LiDAR. An histogram thresholding method and a spectral shape index were initially applied to discriminate shadowed from non-shadowed objects using a QuickBird image. These non-shadowed objects were then divided into vegetated and non-vegetated objects using the NDVI. Through a rule-based classification using the height information from LiDAR data, vegetated objects were classified into “Grassland”, “Shrubs” and “Trees” while non-vegetated objects were distinguished into low and high features. Low features are then separated into “Bare soil” and “Transport units”, again using the NDVI, while tall features were classified as “Buildings” and “High crossroads” using the shape of the objects (density). The developed methodology produced results with an Overall Accuracy of 87%.

SYNTHESIS

A 2.5D / 3D city model focused on buildings can be compiled, through the use of topographic information (e.g., from the land registry), in combination with laser measurement data (e.g., as obtained from a LiDAR flight), and aerial or satellite images. There are several approaches to interpolate and construct a 2.5D urban surface model (incorporating the relief), based on LiDAR and GIS buildings data (e.g., Carneiro et al., 2008; Santos et al., 2010c).

Some authors identify buildings based on a normalized Digital Surface Model (nDSM), produced by subtracting the Digital Terrain Model (DTM) from a Digital Surface Model (DSM) (e.g. Ali et al., 2009; Santos et al., 2010a). Other authors identify buildings in the DSM using features such as local height differences, curvature, height differences, local homogeneity of surface normals, etc. (e.g., Vögtle et al., 2005; Rottensteiner et al., 2003).

5. URBAN PLANNING AND LAND MANAGEMENT IN PORTUGAL

A society's economic development is generally accompanied by a modification of the environment; this implies changes in the way land is used. These changes can be achieved through rehabilitation and re-use of already existing urban areas, or by allocating and transforming non-urban territories. The economic development, and the territorial management, are then two processes that interact. The relation is two-fold: concerted but also conflicted. In fact, the sprawl of urbanization not only results in direct habitat loss, but also generates additional pressures on the existing biodiversity. Furthermore, the growth in urban population implies an increasing demand for food supplies, leading to additional pressure over the rural areas and the aquifers. Also the land-surface impermeabilization, allied with the concentration of buildings and human activity influences locally the air quality and the environmental conditions, contributing to the development of phenomena such as smog or increasing greenhouse gas emissions.

The way land is planned and managed represents the national strategy for the future development of the country. Land Planning is the essence of the management of the human interaction with the natural space. It is a process that seeks to integrate public policies with a balanced social and economic development, to improve the quality of life without compromising the preservation of natural resources. Land Planning includes a series of instruments that impose restrictions, constraints and penalties as well as promotes actions to guide people's behavior in order to pursue the nation's development goals.

In this chapter, the Portuguese Land Planning System at the local level is described. The main instruments for implementing this system are characterized, as well as the cartography that is required for their preparation. Furthermore, a survey on the need and value of geographic information for the municipalities is presented and its conclusions are discussed.

5.1 LAND PLANNING SYSTEM AT THE LOCAL LEVEL

The concerns with land planning are very recent in Portugal. In 1977, the municipal planning starts to be addressed with the publication of Law 79/77, October 25, which defines the attributions of the local authorities and the competences of their bodies. This law was not intended to regulate land planning, but it recommended that the city council could deliberate over the master plan, and ordering its preparation if necessary. The instruments of local land planning available were then the Urbanization Plans that, as their name indicates, covered only the urban territory. Only in 1982, with the Decree-Law (DL) 208/82, May 26, the Master Plans (PDM) are conceived for the local level. The PDM covered the whole territory of a municipality, and not only the urban areas as in the Urbanization Plans. The PDM's production was still voluntary, and it was technically very complex (Alves, 2007). The cartographic elements included a map from the region, with the corresponding regional plan, when existing; a map with the present situation and a map representing the urban structure and the proposed municipal zoning.

The PDM's formalization was based on official cartography. For scale 1:25 000, military maps in analog format were accessible. Regarding the scale 1:10 000, only 19 sheets from Lisbon and 1 from Sagres were available at that time (Guedes, 2003). Consequently, only four municipalities, among 298, had their PDM published during the 1980's (Simões, 2007). Carvalho (2005) points out the existence of a gap between the socio-economic goals foreseen in DL 208/82, May 26, and the effective power municipalities had to develop and attain those goals.

In fact, in Portugal, the land management instruments were still very limited until the country joined the European Community - now EU - in 1986 (Alves, 2007). The admission lead to the adaptation process of both government structures and procedures, either at national and sub-national levels, in order to meet the EU policy-making requirements, and to gain access to structural funds. In 1990, the DL 69/90, March 2, provided a new framework for the PDM, and empowered the municipalities in this matter. In its preamble, the DL 69/90, March 2, states that the revision of DL 208/82, May 26, is necessary because "a land use plan should ensure the participation of the population, integrate the approved policies, have simplified mechanisms for adjusting to new situations, be an instrument whose technical content matches what is actually necessary to ensure the seriousness of the included proposals, and ultimately link up with other instrument tools of the same planning nature".

The new legislation creates a trilogy of plans for the municipal level. The municipal plans include the PDM, which covers the municipal territory, the Urban Plan (*Plano de Urbanização* – PU) designated for the urban areas and the areas to be urbanized, and the Design Plan (*Plano de Pormenor* – PP) that addresses in detail the areas in the PU.

The DL 69/90, March 2, was crucial to increase the number of PDMs, not only because it made the PDM mandatory, but also by simplifying the process of elaboration in terms of content and procedures (Pereira, 2003). Furthermore, the municipalities were "forced" to produce their PDMs, also in order to access the European structural funds. Consequently, during the 1990's, the PDMs started to be produced nationwide, but this process was very slow and afflicted. This was mainly due to:

– The inability of the technicians for producing the PDMs in such a short notice;
– The difficulty of the LULC mapping complying with the requested map accuracy due to the obsolescence of 1:25 000 military maps and to the inadequacy of that scale for mapping certain land uses like the urban fringe;
– Statistical information not spatially disaggregated, disperse and outdated;
– PDM's ambiguity regarding the delimitation of the National Ecological Reserve (*Reserva Ecológica Nacional* - REN) and the National Agricultural Reserve (*Reserva Agrícola Nacional* - RAN) on 1:25 000 scale maps;
– PDM's ambiguity concerning the criteria used for REN and RAN demarcation.

Consequently, in early 1994, little more than 30 PDMs were operational (Alves, 2007). In order to assist the PDM productions efforts, by 1994, a program financed by the European funds, was created: the Support Program on Computer Management of Municipal Plans (PROGIP). The PROGIP main goal was to support the municipal plans (*Planos Municipais de Ordenamento do Território* – PMOT) framework, facilitating the implementation of the established regulations and rules, encouraging the permanent and systematic updating of the information, and to assess the PMOT execution, regarding the initial objectives and proposals. During its lifetime, the program celebrated protocols with 80% of the Portuguese municipalities (Condessa and Monteiro, 2001).

Furthermore, in 1995, through the DL 193/95, July 28, the principals and rules for the cartographic framework in Portugal, namely topographic and thematic mapping, were legally defined. The topographic mapping production and updating were ensured by the former Portuguese National Geodetic, Mapping and Cadastre Agency (*Instituto Português de Cartografia e Cadastro* – IPCC) and the Army Geographic Institute (*Instituto Geográfico do Exército* – IGeoE). Additionally, the IPCC becomes responsible for homologating the topographic and thematic cartography. Along with the publication of the DL 193/95, July 28, the 1:10 000 coverage of the whole territory was also financed. As a result, between 1995 and 2000 the IPCC promoted the digital map coverage at scale 1:10 000 for the whole country, and at scale 1:2 000 in urban areas. The intention was providing the country with an updated base-map in digital vector format, at large-scale, disaggregated enough to serve multiple users, and easily integrated in a GIS. For this purpose, the IPCC defined the technical specifications for these large-scales. Many municipalities and associations of municipalities, and through agreements with the IPCC (ProCARTA – *Produção de Cartografia Topográfica Oficial a Escalas Grandes*), initiated projects for producing their digital cartography. However, in 2001 only 50% of Portugal mainland was covered with 1:10 000 cartography, 25% of which were produced within ProCARTA (Guedes, 2003).

As a result of the mention difficulties, by 1999 the greatest part of the municipal territory (277 municipalities) was covered with PDMs. The process was only completed in 2003, with all municipalities having an active PDM. Analyzing the PDM framework, Alves (2007) concludes that the average production time of the PDM was five years. These are called 1st generation PDMs. Analyzing the cartography used in those plans, Condessa (2003) concludes that existed lack of semantic, geometric and geographic agreement between the elements that constitute the PDM.

Regarding the land use classification, there was a great diversity of designations, reflecting the absence of clear technical concepts and un-systematized nomenclature (Condessa et al., 2002). Santos (2002), when analyzing the classification system used in 12 PDMs (Amadora, Lisbon, Loures and Odivelas, Mafra, Moita, Palmela, Setúbal, Vila Franca de Xira, Almeida, Bragança, Reguengos de Monsaraz and Vila Real de Santo António), found that some cities had simply followed the guidelines of the legislation (“built-up”, “urban”, “industrial activity”, “extractive industrial activity”, “agriculture”, “forestry”, “cultural and natural”, and “vacant land”). While others, the majority, aggregated or disaggregated the classes (“urban and building”, “agricultural and forest areas”, “cultural”, “natural areas”), or used different names but with similar contents (e.g., “no building space”, consisting of agricultural areas, forestry, natural and cultural areas). Several plans have introduced new classes of space to respond to the specific territory (such as “tourist space”, “urban space”, and other equipment).

Regarding the geometry, it was noted that the same information, mapped in the Zoning and in the Constraints Master Plans, had different geometry, different location and were in different numbers. This was visible when it comes to REN and RAN delimitations, but also when administrative limits were mapped.

Regarding the geographic characteristics of the plans, the majority of the PDMs used the 1:25 000 military maps as the basis for their cartography, followed by the IPCC’s 1:10 000 maps, and a reduced number used other scales. Great part of the PDM’s cartography corresponded to the original scale of the base map, but some maps resulted from enlargement and reduction through photo-copying of the base cartography. This situation led to the existence of different map-scales in the same plan, and different map-scale between the Zoning and the Constraints Master Plans. Furthermore, 99% of the mapping framework was in analog format, also leading to multiple distortions and errors.

In 1998 a vital component of the Portuguese planning legislation was approved, the Urbanism and Planning Policy Framework Law (*Lei de Bases da Política de Ordenamento do Território e Urbanismo* – LBPOTU) (Law 48/98, August 11). LBPOTU establishes bases, principles and objectives for territorial management and urbanism. LBPOTU was complemented in the following year, by DL 380/99, September 22, that allowed implementing the land use planning system in Portugal. The LBPOTU creates a land planning system that operates at three territorial levels (national, regional and local), and is accomplished by national, regional and local Territorial Management Instruments (*Instrumentos de Gestão Territorial* - IGT), defined in the DL 380/99, September 22 (with the amendments introduced by DL 53/2000, April 7; DL 310/2003, December 10; Law 58/2005, December 29; Law 56/2007, August 31; DL 316/2007, September 19; DL 46/2009, February 20; and DL 181/2009, August 7). The LBPOTU then defines the types of instruments and the hierarchical relationships between them, their legal status and the competencies of public authorities.

The IGT for the local/municipal level is the PDM. The PDM establishes the basic classification and qualification of land, and construction densities in accordance with local infrastructures, but when it comes to zoning for building purposes, PDMs divide the municipal area into two main categories of land use: urban or rural. It should be noted that the nomenclature appear in the DL 380/99, September 22, as suggestion.

Rural land refers to all land for which is recognized suitability for agricultural activities, livestock, forestry and minerals. It also integrates natural or recreational areas, or land occupied by infrastructure that do not confer the status of urban land. Rural areas are then integrated into the following categories (Article 73º, DL 380/99, September 22):

- Agriculture or forest areas allocated to production or preservation;
- Mining areas;
- Spaces allocated to industrial activities directly related to the uses mentioned in the preceding paragraphs;
- Natural spaces;
- Spaces for infrastructure or other types of human occupation that does not involve classification as urban land, including allowing multiple uses in activities compatible with agricultural, forest or natural areas.

Urban land is defined as land which has a recognized role in the process of urbanization and construction, including already urbanized areas or areas planned to be urbanized, that together constitute the whole urban perimeter. Land is qualified as urban if is incorporated in one of the following categories (Article 73º, DL 380/99, September 22):

- Urbanized land;
- Land programmed for construction;
- Land allocated to the ecological structure needed to balance the urban system.

The LBPOTU (Law 48/98, August 11, with the amendments produced by Law 56/2007, August 31), introduced innovative concepts regarding the planning system in Portugal (Campos, 2008; Simões, 2007):

- The notion of "*land planning and urbanism policy*";
- The notion of "*territorial management system*" and its instruments;

- The duty of regulating land use, the principles and objectives of the "*land planning and urbanism policy*";
- The requirement for regular evaluation of the policy on land planning and urbanism, and the IGT, through its monitorization.

The Judicial Regime of the Territorial Management Instruments (*Regime Júridico dos Instrumentos Territoriais de Gestão* – RJIGT) (DL 380/99, September 22, with the alterations operated by DL 316/2007, September 19) also had an original character, introducing the followings notions (Campos, 2008):

- The technical basis of the solutions proposed by the IGTs is required by law;
- The right to information and participation;
- The principle of identification, grading and harmonization of interests;
- The notion of "*land resources*" and the principle of its identification, protection and valorization of the IGT;
- The duties of internal and external coordination of public entities in the IGTs' developing;
- The duty of mutual compatibility between IGTs.

When the LBPOTU and the RJIGT were approved, 277 PDMs were already ratified (Simões, 2007), meaning that this new legal framework had only applicability for the following generation of plans.

All 1st generation PDMs have already reached their legal term (i.e., 10 years), and are now under revision or have already finalized the revision process. The production of the 2nd generation of plans is based in a different legal framework than the 1st generation, i.e., the Law 48/98, August 11, and the DL 380/99, September 22 (and consecutive amendments). The plans' preparation follows also a different dynamic, mainly due to the demanding for public participation during the plans' production and the plan's monitorization. Also the amendments made to DL 380/99, regarding the instruments preparation, had an impact in the PDM framework.

Among the recent legal tools regarding the plans' preparations, the following stand out:

- Law 56/2007, August 31, the fourth alteration to the DL 380/99, states that the PDMs must become digitally available in the municipality Internet site, and any alteration introduced by the larger-scale plans (Urban and Design Plans) must be reflected and updated;
- Regulatory Decree (DR) 9/2009, May 29, establishes the technical concepts, in the domains of spatial planning and urbanism, to be use in the IGTs, contributing for greater effectiveness and efficiency in land management;
- Regulatory Decree (DR) 10/2009, May 29, defines which cartography shall be used in the preparation of the IGTs, and clarifies the positional accuracy for the base-maps used for plans' preparation;
- DR 11/2009, May 29, that regulates the land use classification provided in DL 380/99. It defines the criteria for land classification into urban or rural, its reclassification, as well as the criteria and classes that qualify the urban and the rural land.

Furthermore, the production of large-scale base cartography (i.e., topographic and thematic maps) mainly from the private sector, now more mature than in the past two decades, allowed the "cartographic support" of the PDMs' revision process.

During the last decades, the PDM's framework has gone through several changes. During the 1st generation of PDMs, Law 69/90 prevailed while the 2nd generation was based on the LBPOTU and RJIGT. The publication of the National Program for Planning and Territorial Management (*Programa Nacional de Planeamento e Ordenamento do Território* – PNPOT), a strategic plan concerning territorial development instruments on the national level, that gives the most relevant options for the territory organisation, by setting up general directives for the implementation that must be considered as a reference for the elaboration of the PMOTs. Figure 27 presents a time-line with the most relevant legal instruments and the programs that characterize the 1st and the 2nd generation of PDMs.

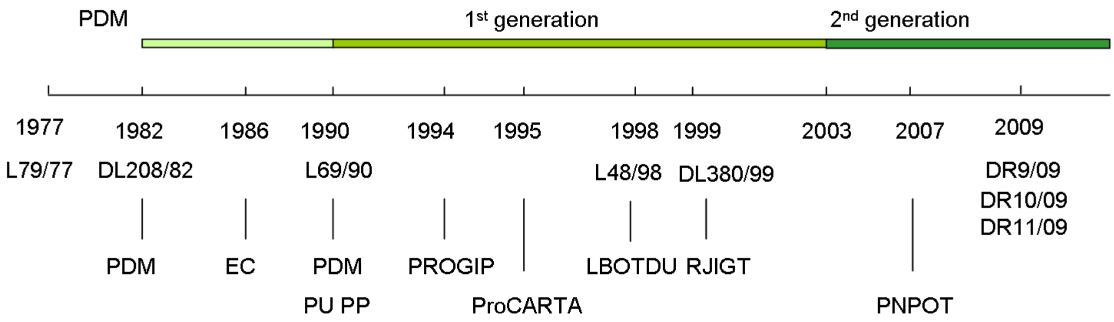


Figure 27. Most relevant legal instruments and the programs that characterize the 1st and the 2nd generation of PDMs

5.1.1 National Entities Involved in the Land Planning Process

To characterize the land planning system, besides identifying the IGTs, and the territory level of applicability of each instrument, it is also important to know what the aim of each instrument is, and which public entities are responsible for its production and approval.

After joining the EU, the central state policy-making structures were oriented in order to accomplish European determinations concerning access to Structural Funds and to improve the effectiveness of their application for promoting regional development. This organization included the following actions (Rato and Rodrigues, 2003):

- Adaptation of the central government organic structure to the requirements of regional development;
- Creation of decentralized administrative bodies dedicated to promote regional development policy;
- Implementation of specific entities in charge of coordinating the access, the management and the control of EU funds, either at national or local levels;
- Implementation of specific units, which included representatives of the private sector and of municipalities for managing regional programs;
- Implementation of advisory bodies, which included experts and representatives of the civil society, for the elaboration and the monitorization of regional development planning.

This re-structuring effort resulted in the actual Portuguese land planning system. Nowadays, Portugal has, in terms of organizations and stakeholders, a hierarchy, with the government at the top. The national, regional and local planning strategies are defined and executed by different actors.

The governmental department who is responsible for defining, executing and coordinating environmental policies, territorial and urban management and regional development, as well as coordinating the national cohesion policy, with the perspective of sustainable development and territorial unity, is the **Environment and Territorial Management Ministry** (*Ministério do Ambiente e do Ordenamento do Território* - MAOT). Connected directly to this ministry, the **General Directorate of Territorial Management and Urban Development** (*Direcção-Geral do Ordenamento do Território e Desenvolvimento Urbano* – DGOTDU).

The DGOTDU is the national authority for land planning and urbanism, and is responsible for the execution of territorial management and urban policies, and for promoting their implementation and evaluation in the national territory. The DGOTDU's main activity (DR 54/2007, April 27) is to support the definition, accompanying and evaluation of public policies in the field of territorial management and urban development. Within this regulation, new responsibilities emerged: regular monitoring and evaluation of territorial management system; normative and regulatory functions providing orientation and technical support on territorial transformations; benchmarking and workshops in the fields of instruction, information and disclosure; and the organization also represents the country internationally (Cardoso, 2009). The DGOTDU is responsible for defining and implementing the PNPOT. PNPOT is effective since September, 2007 (Law 58/2007, September 4). It is a strategic plan that concerns the territorial development instruments at the national level, establishing the national options with special relevance for territorial management, and has become the reference instrument for the production of the regional plans (*Plano Regional de Ordenamento do Território* - PROT).

Commissions for Regional Development (*Comissão Coordenação para o Desenvolvimento Regional* – CCDR) are delegations from the MAOT, that have administrative and financial autonomy, charged to execute, at the level of its geographic area of intervention (Nomenclature of Territorial Units for Statistics II - NUTS II), the policies of regional and urban development, environment, territorial management, nature and biodiversity conservation, sustainable use of natural resources, urban renewal, regional strategic planning and support to municipalities and its associations, pursuing an integrated development of each region. CCDRs are responsible for elaborating and implementing the regional plans (PROT) and all the municipal decisions regarding planning must be presented to and approved by these commissions.

The PNPOT, together with the PROT are plans having strategic nature since they define the most relevant options for the territorial management, by setting up general directives for its implementation.

The **Municipalities** are responsible for implementing the PMOT. These plans have a regulative nature and establish the land use, define evolution models for human occupation, network organization and urban systems. In the elaborations of the PMOTs, the PNPOT and the PROT must be considered as a reference.

Besides the above mentioned entities, the **CNIG**, a governmental research centre, had also an important role in the development of local competences for implementing the PMOTs. The CNIG was created in 1986 (*Despacho* 33/SEIC/86), with the mission of coordinating and implementing the National Infrastructure for Geographical Information (*Sistema Nacional de Informação Geográfica* – SNIG), the Portuguese geographic information infrastructure. The main goal of SNIG was to ensure the connection of Portuguese users and producers of digital geographic information through a network (Hipólito et al., 1999). By 1994, along with PROGIP, the Support Program for the Creation of Local Nodes of SNIG (PROSIG) was also created. Both programs were CNIG's responsibility. The PROSIG was, in a first instance, intended for encouraging the creation GIS in the municipalities, but also to promote their modernization. The PROSIG permitted the acquisition of equipment (hardware and software) and services to support the municipal GIS. The program finished in 1999 and celebrated protocols with 63% of the municipalities (Condessa and Monteiro, 2001).

By 2002, CNIG was merged with the IPCC to form the **IGP**. IGP is now the National Authority of Geodesy, Cartography and Cadastre. IGP is the body responsible for implementing the policy of geographic information in Portugal.

5.1.2 TERRITORIAL MANAGEMENT INSTRUMENTS APPLIED IN THE LOCAL LEVEL

The LBPOTU organizes, in a coordinated interaction framework, the territorial management system in three hierarchical levels: national, regional and local. In 1999 the system's rules were established by the RJIGT (DL 380/99, September 22), which defines the coordination framework of its three levels, the general land use regime and the procedures to be followed in the preparation, approval, implementation, review, and assessment of the territorial management plans. Given the scope of this thesis, the following discussions will be focused in the local level, and its instruments.

Land-use planning and management is a direct responsibility of the local authorities. The land use municipal plans – PMOTs – are thus prepared, approved and implemented by the municipalities. These territorial planning tools are regulatory instruments that establish the land-use regime, define the population growth distribution, the infrastructure and the facilities' networks and the urban system organization models, as well as, depending on their scale, the land use parameters/indicators/guidelines. These tools constitute the framework through which the municipalities implement their planning police. The PMOTs set arrangements for the conversion of the guidelines defined by national and regional strategic instruments to a smaller scale, which expresses, territorially, a local development approach. The PMOTs include three large-scale types of plans:

- Master Plan (PDM) – defines the organization of a municipal area, constitutes a synthesis of the local development and management strategy, and locally integrates the options of the major national and regional plans. It constitutes the long-term basis for the municipal investments' planning, thus spatially representing the development options. The PDM establishes the spatial structure of the municipal territory, defines the baseline land classification, as well as parameters/guidelines for land use, defines the location of social facilities, and implements the classification of rural and urban land. Furthermore, the PDM defines the areas reserved for future urban expansion, the areas where urbanization is a priority, the areas where urbanization is not allowed as well as activities that significantly alter the configuration of the territory, and the areas reserved for infrastructure deployment. The map scale of the PDM is 1: 10 000 in urban counties and 1:25 000 in rural ones;

- Urbanization Plan (PU) – defines and implements the spatial organization of areas classified as urban in the PDM. Furthermore, the PU sets the urban indicators and urbanization parameters, the patrimony values to be protected, the locations for implementing facilities, the delimitation of road network and the main infrastructures, and the municipal vacant land. It also establishes operational planning and management sub-units that will provide the basis for the Design Plans. The map-scale is 1:2 000 to 1:5 000 (in exceptional cases, 1:10 000);
- Design Plan (PP) – implements spatial organization proposals, by defining and detailing the design of land use. The PPs are also used as a pillar for the execution of infrastructural projects, buildings' architecture and also exterior spaces, according to the PDM and PU. This is the plan with the larger scale – 1:1 000 (exceptionally 1:2 000).

It is important to note that both PU and PP change the PDM, because they update and implement new territorial organizations or classifications.

The revision of these plans can occur 3 years after their approval, and is mandatory after 10 years (DL 380/99, September 22), but they are valid until the approval of new modifications or a review.

5.1.3 Formalizing the PDM

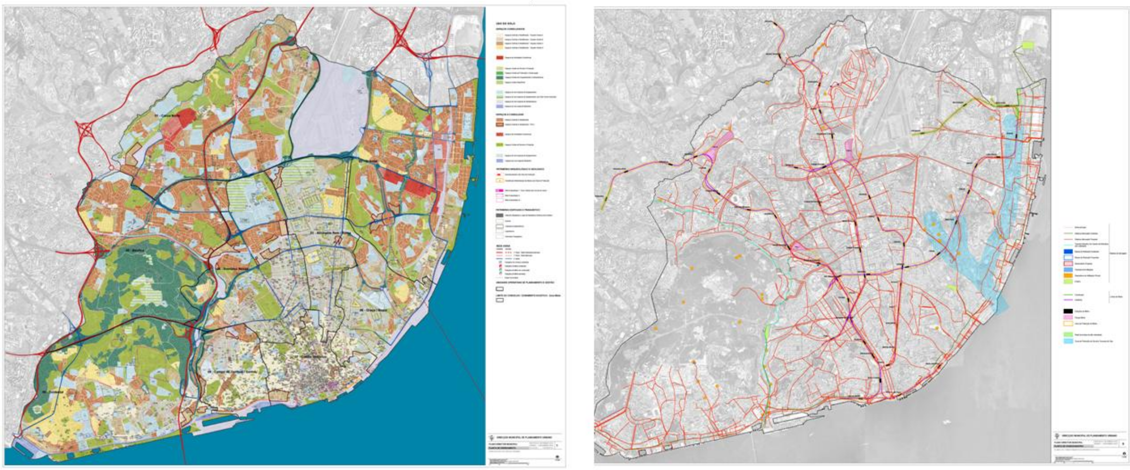
The formalization of the PDM is made through its constituent elements, and accompanying elements. The constituent elements of a PDM, as defined by the DL 380/99, September 22, and the Ordinance (*Portaria)* 138/2008, February 2, are:

- Regulations;
- Overview regional map, produced at a smaller scale than the PDM, with indication of the adjacent municipalities, most important cities, main roads and other relevant infrastructure and large facilities that serve the municipality, and the delimitation of the area of intervention of other land management instruments in action in the municipal area;
- The Zoning Master Plan (*Planta de Ordenamento*) that represents the municipal spatial structure, according to the classification and the qualification of land, as well as the operational planning and management units defined;
- The LULC map depicting the current situation;
- The municipal ecological structure map;

– The Constraints Master Plan (*Planta de Condicionantes*) that includes: administrative servitudes and public utility restrictions (*Servidões Administrativas e Restrições de Utilidade Pública*), and the map of constraints and infrastructures. One type of constraints includes the ecologically sensitive areas and prime agricultural soils that are under specific regulation (e.g., REN and RAN). Each of these areas has to be delineated in the Constraints Plan. Specific features like rivers, reservoirs and buffering zones, erosion zones or soils with agricultural potential, must be mapped. Also constraints of sprawl and of urban expansion areas are represented in the plan;
– Report or map indicating the licenses or authorizations of urban operations issued and the prior favorable information in force, replaceable by declaration of the city hall proving the absence of those urban commitments in the area of the plan;
– Comments and reviews received in the public discussion phase and respective report with their weighting.

Other elements also accompany the PDM: descriptive studies that characterize the physical, economic and social aspects of the municipal area; a program containing information on predicted intervention and executions as well as their financing; and a report that justifies the options adopted within the plan.

Figure 28 shows the Zoning and Constraints Master Plans, proposed for public discussion under the Lisbon's PDM revision.



*Plans in proposal stage

Figure 28. Lisbon's PDM Zoning Master Plan and Constraints Master Plan (source: Lisbon City Hall)

5.2 MUNICIPAL PROCEDURES THAT REQUIRE GEOGRAPHIC INFORMATION

The PDM needs to go through a series of steps, before being a legal instrument. The steps for producing and revising a PDM are: (1) preparation, (2) participation, (3) companion, (4) conciliation procedure, (5) public discussion, (6) final advice from the coordination committee, (7) approval, (8) final control, (9) registration and ratification procedure to guarantee compliance with the legislation in force, and (10) publication in the official journal. The plan becomes effective only after these procedures.

5.2.1 PDM Preparation

Most of the information used within the local planning has a geospatial component. This geographic information is formalized through cartographic representations like topographic and thematic maps. Topographic mapping depicts the form of the Earth's surface, most commonly expressed as elevation above sea level, and also includes features such as watercourses, vegetation, buildings, roads, power transmission networks, etc. Non-topographical geographic information (e.g., demographics, exposure to sunlight, rainfall, suitability for construction, etc.) is called the thematic information and their representation on a topographic base is called thematic cartography.

The elements that constitute the base-maps used in the preparation of the PDM are described in the technical specifications, published by the IGP. The IGP is the national institution responsible for approval of the 1:10 000 maps. These large-scale maps constitute the base-information for producing the topographic and thematic layers that appear in the PMOT.

The elements of the PDM that are supported by thematic cartography, according to the DL 380/99, September 22, and the *Portaria* 138/2005, February 2, are all the constituent elements of a PDM (section 5.1.2).

During the process of revising the PDM, several municipalities pointed the outdated cartography as an aspect that complicated the plan’s management, promoting the review process. Another factor that contributed to the plan’s lack of efficiency was the use of military maps (scale 1:25 000) as base-maps, which at the time of the plan’s preparation were already outdated. The cartography being available only in analogue format also hampered its update.

The IGP effort with the project ProCARTA, resulted in a mapping framework performed according to a standard, i.e., the indicated specifications. This effort was legally reinforced (DL 380/99, September 22, with the amendments introduced by DL 310/2003, December 10 and the DR 10/2009, May 29) by making mandatory the use of official cartography (i.e., produced by official authorities), or approved cartography when preparing the PDM.

Along with the effort of promoting a standard cartography, the DGOTDU also promoted the harmonization of all the symbology used in the PDM's cartography.

The topographic maps required for the preparation of the PDM, are generally produced based on aerial images, photogrammetric methods and field work. This methodology allows mapping information with the detail indicated by the IGP's catalogue of objects, and the positional accuracy of the respective scale. However, this is a very time-consuming procedure, which also demands a great financial effort by the municipality. Nevertheless, it is a very accurate process that can not be replaced. Satellite images or LiDAR data are other sources of information on the land status, which can also be explored in order to produce the desired geographic information for PDM's preparation. Figure 29 shows the online service, where the maps included in the PDM proposal are available for the general public.

Lisbon's PDM in revision: Web-mapping service with the plan's proposals

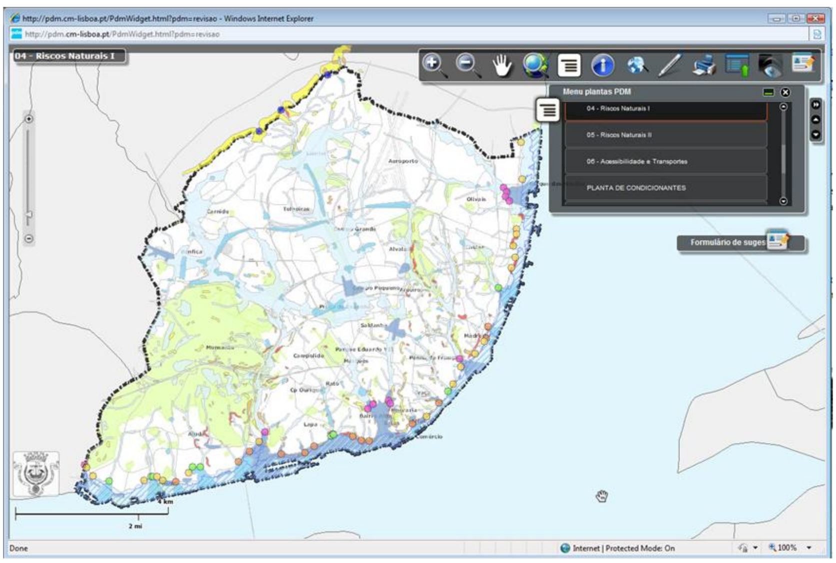


Figure 29. Lisbon's PDM revision (source: Lisbon City Hall)

5.2.2 PDM PUBLIC DISCUSSION

Every citizen concerned as well as associations representing the economic, social, cultural and environmental interests, have a right to participate in the process of preparation, amendment, review, implementation and assessment of the different territorial management plans, namely through the consultation of the documents that justify the proposals, the possibility to get copies of the proceedings of deliberation meetings and certificates of the adopted plans, being informed about the plans' provisions, as well as about the constraints pertaining the land use.

The public bodies responsible for the preparation, amendment, review, implementation and assessment of the different plans have to make public, namely through media outlets, the decision to start the procedures mentioned above, the end of each of those procedures and the documents to be submitted to public discussion, and the opening and timetable for the consultation. Afterwards, when the period for public discussion ends, the results of the plan's public debate have to be considered in the final draft proposals submitted for approval.

An effective way of presenting the PDM's proposal is through visualization of its contents in a GIS (González et al., 2008). Displaying data like a 3D model of the city overlaid on aerial or satellite imagery, transmits to the people a realistic piece of information. Public Participation GIS (uses and produces digital maps, satellite imagery, sketch maps, and many other spatial and visual tools, to change geographic involvement and awareness at a local level. The infrastructure itself may help identify or provide information about neighborhood problems and their solutions. It may include predictive models or scenario-building techniques that can help forecast the effects of policy decisions on the quality of life of urban residents. The geographic information infrastructure, can act as a "facilitator" to help with communication between policy makers and communities about local conditions and opportunities, viewed geographically (Rugg, 2003).

Another possibility is to distribute information through the Internet. This is a rapid and useful way of informing and involving the public. In fact, the popularization of the Internet has had an enormous impact on geographic information technologies, and has opened the potential for new visions of a geospatially enabled world (Goodchild, 2006). The popularity of public geographic platforms like Google Earth or

Microsoft Service Network maps is a good example. Through web mapping, information can be supplied by attaching a Uniform Resource Locator (URL) to a particular location on the map, and an opinion about a decision concerning that location can be recorded. Maps are seen as a central tool in this environment, serving as both information repositories and vehicles for communication. MacEachren (2001) identifies three type of maps that can be used within computer-supported decision-making: annotation maps (enabling comments by users), argumentation maps (that support negotiation and discussion by integrating information and arguments in a map-based display), and alternative maps (that depict possible scenarios).

Three national examples of such electronic public discussion were carried out for Oporto's PDM, in 2004, PROT-OVT, in 2008, and PROT-AML, in 2011. A collaborative online platform was created for this purpose, where it was possible to receive input and discuss the plan among members of both the coordinator commission and of sector teams. From the Oporto's PDM public discussion, 459 registered users exchanged 813 messages regarding the plan's proposals, and 66% of new proposals were made through this media (Oliveira et al., 2004). For the PROT-OVT, more than 150 contributions were received since the entry into operation of the platform, while for PROT-AML public discussion, the electronic platform received 55 contributes.

5.2.3 Assessing and Monitoring the PDM Implementation

The 1st generation of plans followed a hard approach, where the zoning process conferred little flexibility towards the determinations of urban and non-urban areas. The 2nd generation already foresees the land planning as working in progress, attempting to regulate the land changing process, rather than constrain it. The DL 380/99 creates, as already foreseen in LBPOTU, a controlling mechanism for the IGTs' implementation, evaluation of its adequacy and concretization. As a result, every two years, each municipality must produce the Status Report of City Planning (*Relatório do Estado do Ordenamento do Território* - REOT-M). The REOT-M contains the execution of the PMOTs, its articulation with the municipal development strategy and may address the possibility of revision or change. In this case, the report should focus on the levels of implementation, on the evolution of the main indicators characterizing the municipality, its environmental quality, and should define new targets for the development of the municipality and the sustainability criteria to be adopted. The monitorization aims at evaluate *in continuum* the plan's implementation, the longest procedure of the planning process (Pereira, 2009). The monitorization can be done from two perspectives: evaluation of compliance (considering the correspondence between the actions and intentions/ objectives of the plan), and evaluation of performance (incorporates the former and focuses on the role that the plan plays as reference for decision making) (Pereira, 2009).

According to Baptista e Silva (2003), the planning assessment process involves the following analysis:

- The evaluation of results obtained through the plan and their intended actions;
- Consider whether the objectives and strategies of the plan continue to make sense;
- Study the behaviors and trends that may question what the plan establishes or that compromise the plan's success;
- Consider the means, resources, mechanisms, solutions and options set out in terms of the planning process.

Questions like "Does the Plan reflect the reality of the municipality?", "Was it implemented? If so, did it meet its goals? If not, why?" are issues that must be considered in the monitoring process.

REOTs are generally based on environmental indicators of three types: pressure, status and reply. The pressure indicators characterize the demands upon environment systems, and include ratios like impervious area per capita. The status indicators reflect the quality of the environment over a given space/ time horizon, and include sensitivity and risk indicators. The reply indicators evaluate the society's responses to changes and environmental concerns, as well as adherence to programs and/ or implementation of environment-friendly measures. This group includes sensitization and awareness indicators, or activities of important social groups.

Other initiatives that pursue the monitoring of the land planning in Portugal are the National System of Territorial Information (*Serviço Nacional de Informação Territorial* – SNIT) and the Monitoring Centre for Spatial Planning and Urbanism (*Observatório do Ordenamento do Território e Urbanismo* – OOTU).

SNIT is a nationwide official information system initiated in 2008, which is a responsibility of DGOTDU that supports the provision of public service, and pursues three main objectives:

– To ensure the right to information and the right of public access to territorial management tools and information on its application;
– To be a collaborative system, shared between the authorities responsible for the territorial management, aiming at facilitating the information flow and the decision processes, and consequently the quality of services provided and the effectiveness of the territorial management system;
– Support and encourage the internal reorganization of processes and working methods of DGOTDU, improving its efficiency.

SNIT provides online access to all the PDMs of Portugal mainland as well as two other information products developed by the DGOTDU - the Land Use System Map of the Continent (*Carta do Regime de Uso do Solo do Continente*), the Map of the Landscape Units of Continental Portugal (*Carta das Unidades de Paisagem de Portugal Continental*), and the PNPOT.

The OOTU, also a DGOTDU’s responsibility, is in charge of collecting and processing information of a strategic, technical and scientific character, relevant to the assessment of policy planning, urban development and territorial management system.

The introduction of these assessment tools in the PMOTs’ process of implementation, made the planning monitoring a requirement. However, according to Pereira (2009), in Portugal, the land planning system remains focused on the plan’s preparation. The plan’s implementation is not monitored and evaluated and the results often fall short of the announced (according to empirical evaluations). These conclusions are also supported by a survey on the execution of the PDMs, executed by the DGOTDU in 2006-2007. The results of the survey indicated that the generality of the municipalities has no information that allows monitoring the PDM’s implementation. Furthermore, the municipalities are not able to quantify basic variables such as the urban land available in the municipality territory, the proportion of the land programmed for urbanization that was urbanized between the time the PDMs became effective and the data of the survey, or the number of constructing licenses granted in urban land and/or rural land (Campos, 2008). The same survey concluded that the existing GIS and other information technologies are not used for implementing the strategic management functions or the plans' monitorization but rather for assessing the urban management. Furthermore, Pereira (2009) concludes that the REOT-M are still few, and to the author's knowledge, no municipality has produced its REOT-M within the recommended interval (i.e., biannual). The existing REOTs at the local level have emerged rather as a justification for the PDMS' review, as required by law.

Based on this review, one can conclude that updated information that allows monitoring and evaluating the developments in the territory, is needed.

Adimistrative controls, like identification of illegal construction sites, is one of the outlets for application of EO data. Satellite imagery has the capacity to detect and monitor land change. LULC data sets obtained through remote sensing, allows investigating territorial trends, to identify urban and environmental indicators and serve as basis for developing scenarios of urban growth. Many cities, in fact, use aerial photos to check the compliance of declared work sites to urban development regulations. Furtheremore, besides urban planning, task like administrative, fiscal or legal verifications have been successfully accomplishwed by public authorities through EO data usage. A notable example is found in the agricultural servicies, where declarations of arable surfaces establishing eligibility for the Common Agricultural Policy subsidies have been checked by remote sensing for the past years (Tapsall et al., 2010).

Furthermore, EO data provides a way for guiding land-use policies at the national, regional, and local levels. This information makes government policymakers aware of the large-scale impacts of local activities and provides a means of integrating local knowledge about effective land-use practices into a regional or national land-management framework.

5.3 THE NEED FOR UPDATED GEO-INFORMATION AT THE MUNICIPAL LEVEL

When characterizing the municipalities' attitude regarding geo-information (GI), three major questions arise:

- Is GI used in a regular basis?
- Is it an important resource?
- Is the information's spatial and temporal attributes appropriate for the municipal activities?

Based on the answers to the prior questions, considerations on the **need and value** of updated GI for municipal use can be drawn, as well as assessing the priorities and perceptions of the local government regarding geographical data. With this goal in mind, a survey was designed to characterize the actual level of GI use at the municipal level, and to investigate the needs and how Portuguese municipalities value GI.

The survey was planned for providing valid data for developing accurate estimates for the entire population of municipalities. The execution involved several steps. Firstly, the survey text was designed based on the cited objectives. Then it was put online and an invitation e-mail was sent for all the municipalities. After receiving the completed questionnaires, the data was summarized and statistical analyses were performed. The following sections describe these steps in detail.

5.3.1 SURVEY TEXT

The survey consists of an introductory text and six parts (Appendix 1). The answers generate qualitative information about the topics under examination. Some questions are mandatory and allow multiple choices. Close-ended with or without ordered response categories and partial close-ended questions are present. The survey collects different types of information: people's attitude towards the available and the desired GI, their opinion on the adequacy of the information for the department's activity, their behavior based on the frequency which GI is used, and the influence of people's hierarchic position on the type of GI used.

The executive summary presents the survey context and its goals. Simple fill in instructions and the estimated time to finish are provided. Following the text is the survey questionnaire, comprising six parts.

Part 1 – Characterization of the municipal department

The first part aims at characterizing the service/department. In this identification step it is asked for the service/department name, job position of the respondent, telephone and e-mail (the last two are not mandatory fields).

Part 2 – Use and importance of GI for the municipal activities

The second part addresses the use and importance of GI for the municipal activities and is organized in four questions: whether GI is produced by the department, used, or both, if is it important, for what purposes it is used and with what frequency.

All these are closed-ended questions except for the one related with the intended use, which is partially close-ended.

Part 3 – Sources of GI

This part relates to the main sources of GI used in the department (produced by the department, produced by other municipal services, private suppliers and/or internet). This is a partially close-ended question, with a section where other responses can be written;

Part 4 – Format of the GI used by managers and technicians and its adequacy for the municipal activities

This part characterizes the GI used by the department. Distinction is made between the politicians, middle managers and technicians regarding the most common GI support format used (digital, paper, both). Also the GI adequacy for the department needs is inquired. The four questions are all close-ended questions;

Part 5 – Use of VHR imagery by the municipalities

The fifth part of the survey addresses the use of VHR images (aerial photographs and satellite images) for the department activities. For those affirmative answers, the frequency of usage is asked. When no imagery is used, the inquired is asked if it would be easy or difficult to implement its usage and why (lack of informatics, no human resources, imagery cost or other). These are closed and partially closed-ended questions;

Part 6 – Characterization of the GI used for the municipal activities

The last part of the survey is for characterizing the GI. A distinction is made between the already used GI and the desired GI. Questions regarding the kind of geographic element (e.g., buildings, roads, trees and/or elevation contours), its importance, map scale, update periodicity and type of representation (point, line, polygon or raster) are made for the already used and desired GI. These are closed and partially closed-ended questions´, presented in the form of matrices.

The survey was implemented in a freeware online application, the Google Spreadsheet. This software was chosen for two reasons: it is a free application, and the answers are stored and compiled in a Google Docs Spreadsheet file in real-time, facilitating the analysis. After designing the questionnaire, the survey was published online.

5.3.2 DISSEMINATION

The area covered was the Portuguese territory and the survey units were the municipalities (in a total of 308). All municipalities were contacted via e-mail, with an introductory text and the link for the survey. In the e-mail text, the context of the survey is presented as well as the responsible organization and the Principal investigator. In case of doubts the main contact person in the organization is specified. Confidentiality is guaranteed. Precise orientation for filling in the questionnaire is provided, regarding who should respond - a technician (*técnico superior*) or a senior technical advisor (*assessor*) – from the GIS department, and that the opinion of the department should be reflected in the answer rather than personal judgments.

The survey was distributed on May 18, 2010, and all responses obtained until September 3, 2010, were considered for this analysis. In June a follow-up e-mail was sent to those municipalities which did not reply, to reinforce their participation.

5.3.3 DATA COLLECTION

In order to characterize the success of the data collection, the response rate is used. This index describes the extent to which the data set includes all sampled municipalities. It is calculated as the number of municipalities that returned complete questionnaires divided by the total number of contacted municipalities. The higher the response rate the lower is the sample bias, and more credible are the statistics about the population as a whole.

From the 308 contacted municipalities, 140 replied with complete questionnaires (128 municipalities from Portugal mainland, 3 from Madeira and 9 from Azores). This number represents a response rate of 45%, and means that conclusions about the population can be made with a confidence level of 90% and a margin of error of 5%.

5.3.4 DATA ANALYSIS AND RESULTS

The 140 surveys were analyzed in PASW Statistics 18 (ex-SPSS) and ArcGIS. Three types of analyses were made: univariate, multivariate and spatial analysis. The results of these analyses are presented in the following sections.

Part 1 – Characterization of the municipal department

The total number of municipalities that responded to the survey was 140 (Table 6). Some municipalities (17) provided surveys for more than one service/department. Lisbon had 11 departments responding, Palmela had 5, Setúbal had 3, while 16 municipalities returned responses from 2 departments. The remaining municipalities returned only one survey for one department. In the end, 172 surveys were delivered by the 140 municipalities that completed the survey. When a municipality responded with more than one questionnaire, only one was considered for further analysis. The criterion for selection was to initially choose the survey originating from the GIS departments. When this was not possible, the most similar department was chosen, beginning with Urbanism departments, followed by Environment, Infrastructures and Other departments.

Table 6. Number of completed surveys

	Nº of responses	**%**
Portugal mainland	128	91.4
Azores	9	6.4
Madeira	3	2.1
Total	140	99.9*

* The total percentage does not equal 100% due to rounding

The type of department with more responses was the Urban Planning, with 45.0%, followed by the GIS (32.9%), Environment (11.4%), Infrastructures (1.4%) and Other departments (9.3%) (Table 7). This last group includes departments like Civil Protection, Studies and Projects, or Informatics.

Table 7. Department's response rate

Department	**Nº of responses**	**%**
Urban Planning	63	45.0
GIS	46	32.9
Environment	16	11.4
Infrastructures	2	1.4
Other	13	9.3
Total	140	99.9*

* The total percentage does not equal 100% due to rounding

The majority of people that filled-in the surveys were technicians (73.6%), followed by managers (26.4%).

Part 2 – Use and importance of GI for the municipal activities

The first question concerned the role o f GI in the departments' activities (question 2.1). The production and use of GI was the departments' most common type of response (76.4%), followed by just use (18.6%) and just produce (5.0%) (Table 8).

Table 8. The role of geographic information in the departments' work

GI role	Nº of responses	%
Used	26	18.6
Produced	7	5.0
Both	107	76.4
Total	140	100.0

The municipalities that just use GI, reveal low level penetration of information technologies and human resources less specialized in the department that responded to the survey.

When analyzing the spatial distribution of the responses (Figure 30), an irregular distribution is observed. However, dismissing Palmela, Setúbal and Seixal, we can observe that the municipalities that only use GI are mainly from the eastern and more rural side of the country.

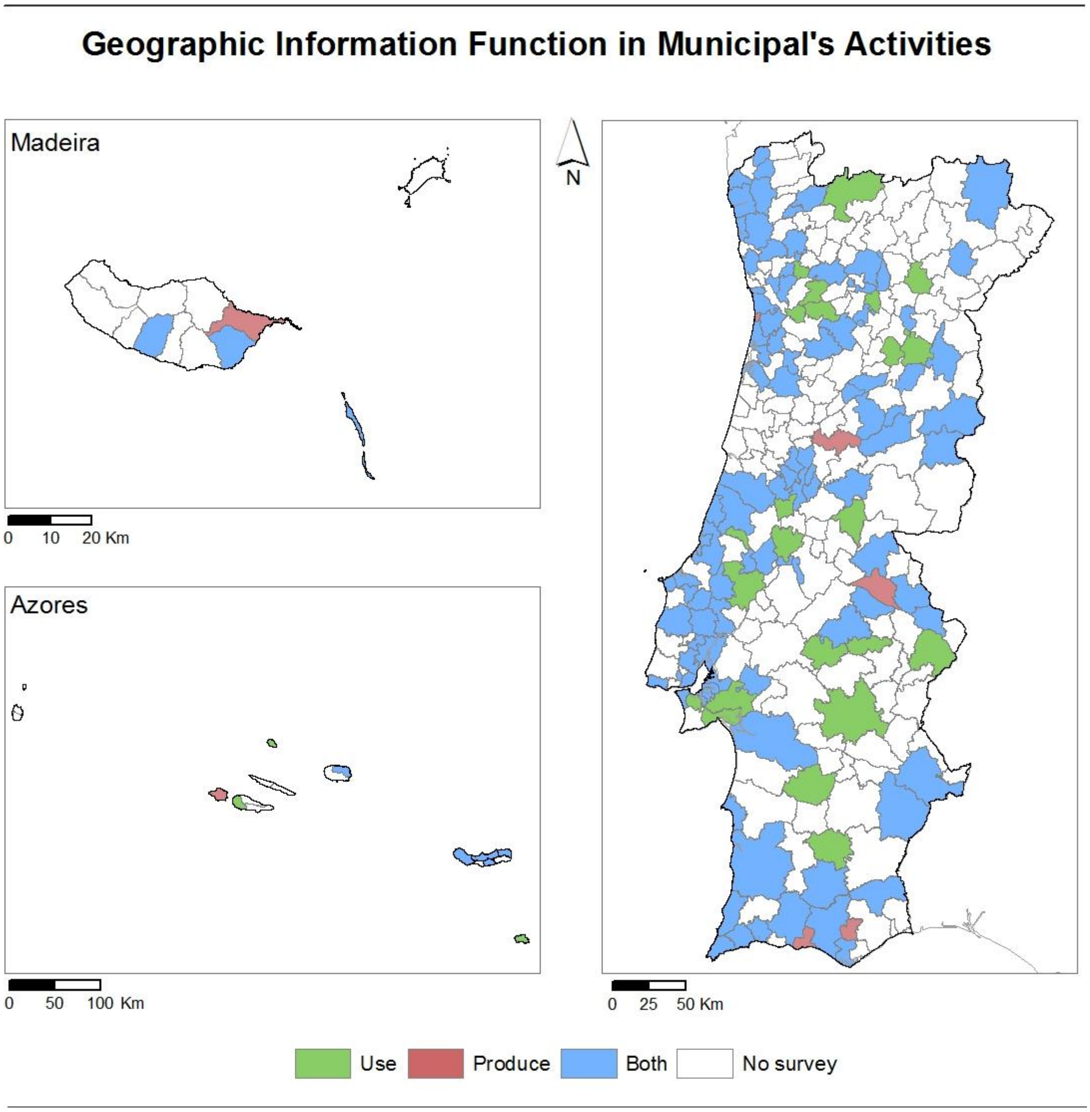


Figure 30. Relation between geographic information and the municipalities in Portugal

When questioned on the importance of the GI for the department's activity (question 2.2), 80.7% respondents considered it fundamental while 18.6% considered it very important, and 0.7% classified it as less important (Figure 31).

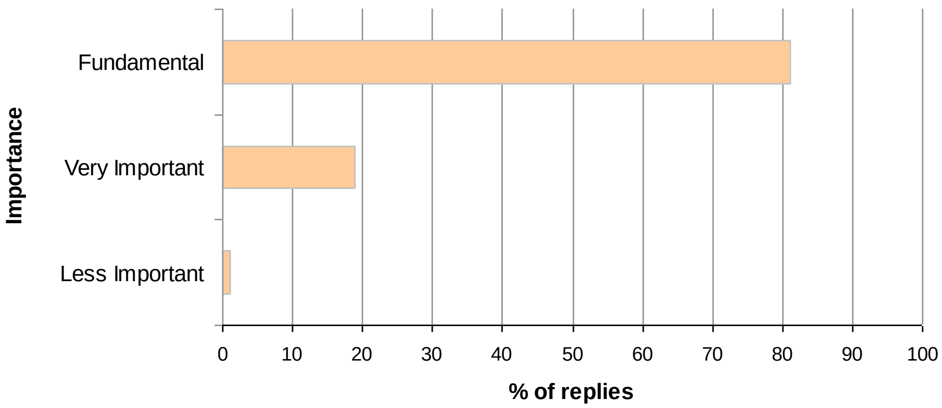


Figure 31. Importance of Geographic Information for the municipal activities

The main use of GI by the departments (question 2.3) is GIS analysis (40.0%), followed by visualization (25.0%) and cartographic production (24.3%). Since this was a multiple-choice question, the remaining answers (10.7%) were different combinations of the above choices. This response rate also reflects the diversity in the usage of GI. A municipality indicated that does not use GI in its activities. In the open-ended section, it was also indicated that GI is used for production of location plans, as base information for map production or PDM revision. When mapping this information in a GIS (Figure 32), once again, no regular distribution of the replies was perceptible.

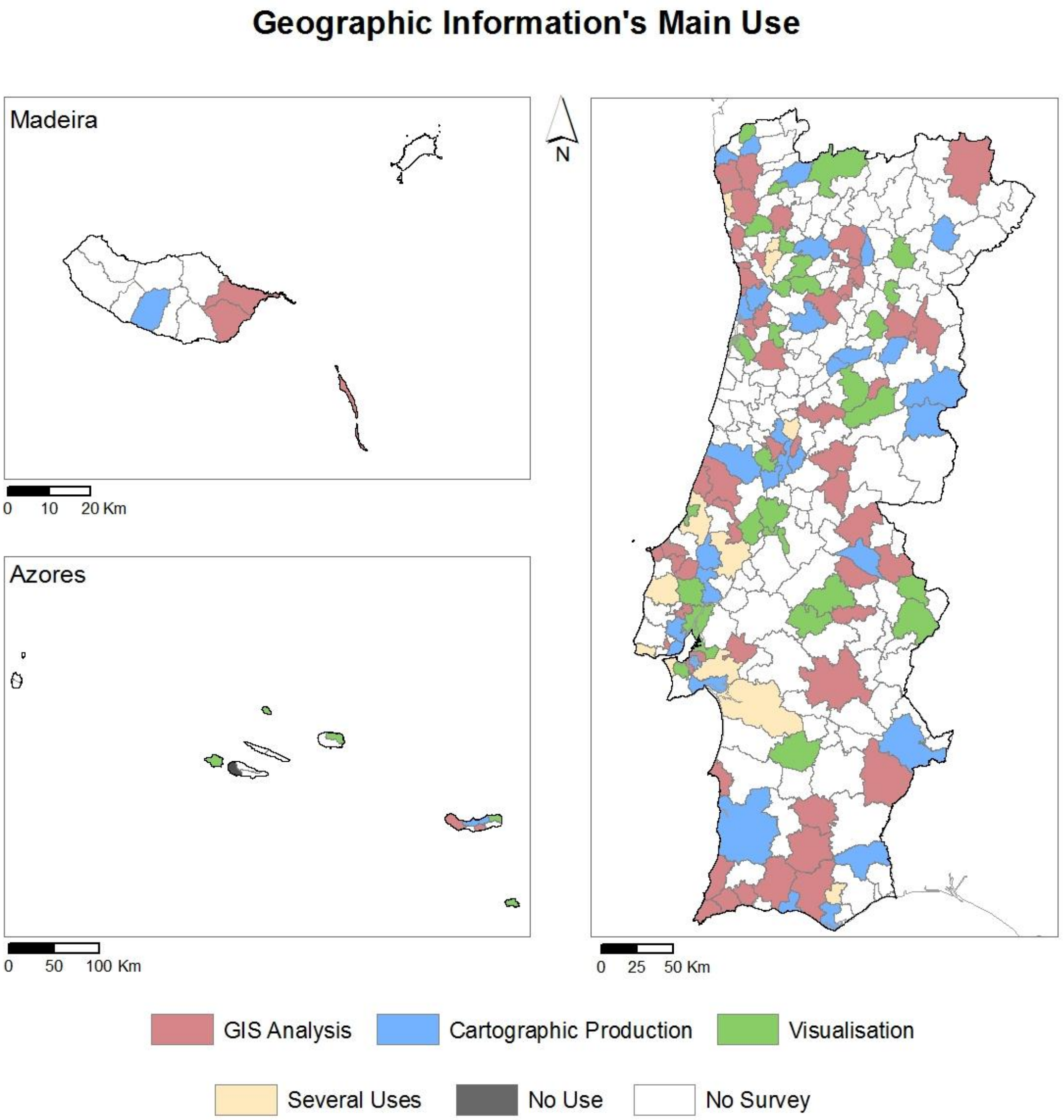


Figure 32. Main use of geographic information in Portugal

When analyzing the type of GI usage (question 2.1) considering its main use (question 2.3), we found that those departments that only produce, and departments that use and produce GI, do it mainly for GIS analysis, while the ones that only use GI do it for visualization purposes (Table 9). We can conclude that, independently of the GI role in the municipality, its main use is analytical and not cartographic.

Table 9. Geographic Information's role in the municipalities and operations it is used in

GI Role	GI Destination%				
	GIS Analysis	**Cartographic Production**	**Visualization**	**Other Combinations**	**Total**
Used	26.9	7.7	53.8	11.6	100.0
Produced	42.9	28.6	14.3	14.2	100.0
Both	43.0	28.0	18.7	10.3	100.0

Concerning the frequency of use of GI (question 2.4), 84.3% of the departments responded that they use it daily, 10.0% use it weekly and 5.0% use it monthly. A municipality (0.7%) replied that despite having GI, it does not use it. The municipalities that make a monthly use of GI are located in the rural side of the country, where the urban pressure is less demanding than in the western side.

Part 3 – Sources of GI

This was a multiple-choice question, and returned several combinations of the sources indicated in the questionnaire. "Department's information", "other department's information" and "other public services" was the most selected choice with 16.4% of the replies. "Department's information" and "from other public services" was selected by 15.0% of the respondents, while 10.7% indicated department's information (Figure 33). In the open-ended section, sources like the municipal associations or related projects were indicated as alternative data sources.

We can conclude that the municipalities produce their own data and also rely on data from other public services (42.1%). Surprisingly, the Internet only appeared in 4th place as a source of GI. On the other hand, as expected, private data providers only account for a smaller segment of the preferences.

From these results, one can assume that GI is not considered a valuable resource, thus not justifying a municipal investment.

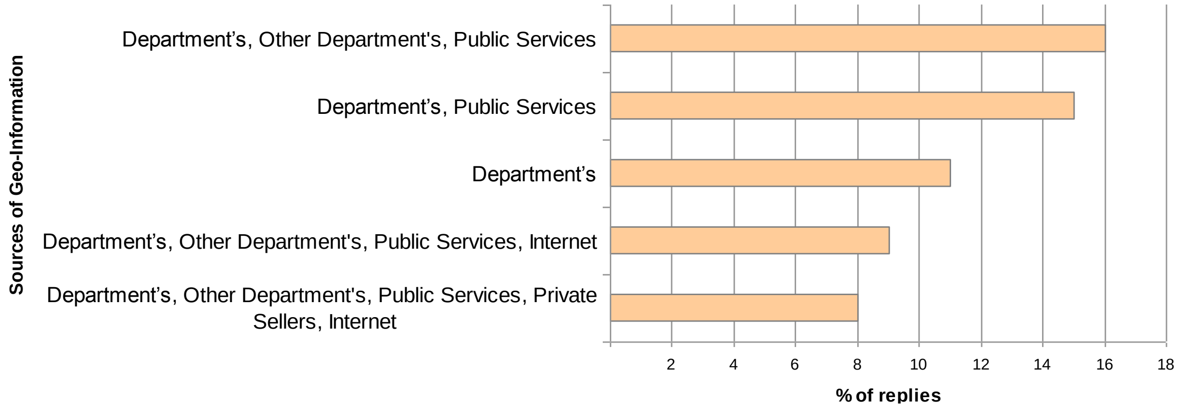


Figure 33. The five main data sources of Geographic Information used by the municipal departments

Part 4 – Format of the GI used by managers and technicians and its adequacy for the municipal activities

On the issue of the most used type of GI support format (question 4.1), 59.3% of the politicians selected paper and 29.3% selected both digital and paper. As for the middle managers, the most common format was also the paper (38.6%), followed by both digital and paper (33.6%). Regarding the technicians, 70.7% of the preferences go for the digital format, followed by both digital and paper (28.6%) and only 0.7% prefer paper format (Figure 34).

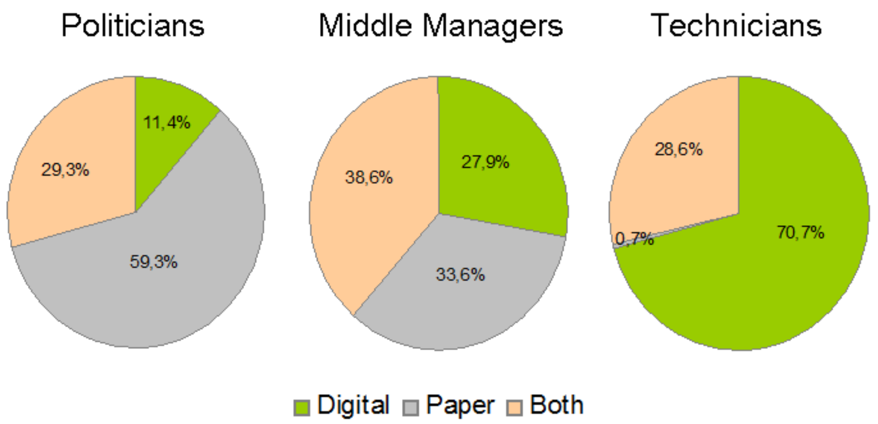


Figure 34. Support format preferred for Geographic Information according to the end-user

On the adequacy of the GI used (question 4.2), 63.6% responded that it was adequate, 20.7% selected very adequate, and 12.9% chose less adequate. GI was found to be inadequate by only 2.9% of the departments.

When relating the municipalities that produce GI (question 2.1) with the adequacy of GI (question 4.2), not surprisingly, the majority replied that it was adequate. The majority of those reporting less adequacy or inadequacy of GI are municipalities that only use, or use and produce GI.

Part 5 – Use of VHR imagery by the municipalities

This section included separate questions for aerial photography and satellite images, in order to infer the level of familiarity with these sources of GI.

Regarding the use of aerial photos (question 5.1), 92.1% of the responses were positive. Among the municipalities that use this type of images, 67.1% use it daily, 18.6% use it weekly and 3.6% use it monthly. The non-users (7.9%), say it is difficult to integrate aerial photography in the department's activities, mainly because of lack of informatics and the data cost.

Regarding the use of satellite images (question 5.2), 22.9% returned affirmative answers, and use it mainly on a daily basis. Of those municipalities that do not use satellite images (77.1%), 47.1% state it should be easy to implement this data in their activities. The ones that responded that it would be difficult (29.3%), pointed the imagery cost as the major obstacle to its implementation, followed by the lack of informatics.

Figure 35 characterizes the municipalities that use optical images and Figure 36 shows their location.

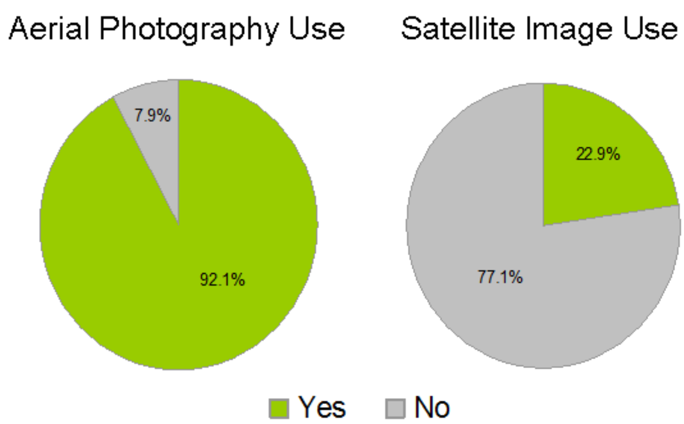


Figure 35. Use (%) of aerial and satellite images by the municipalities

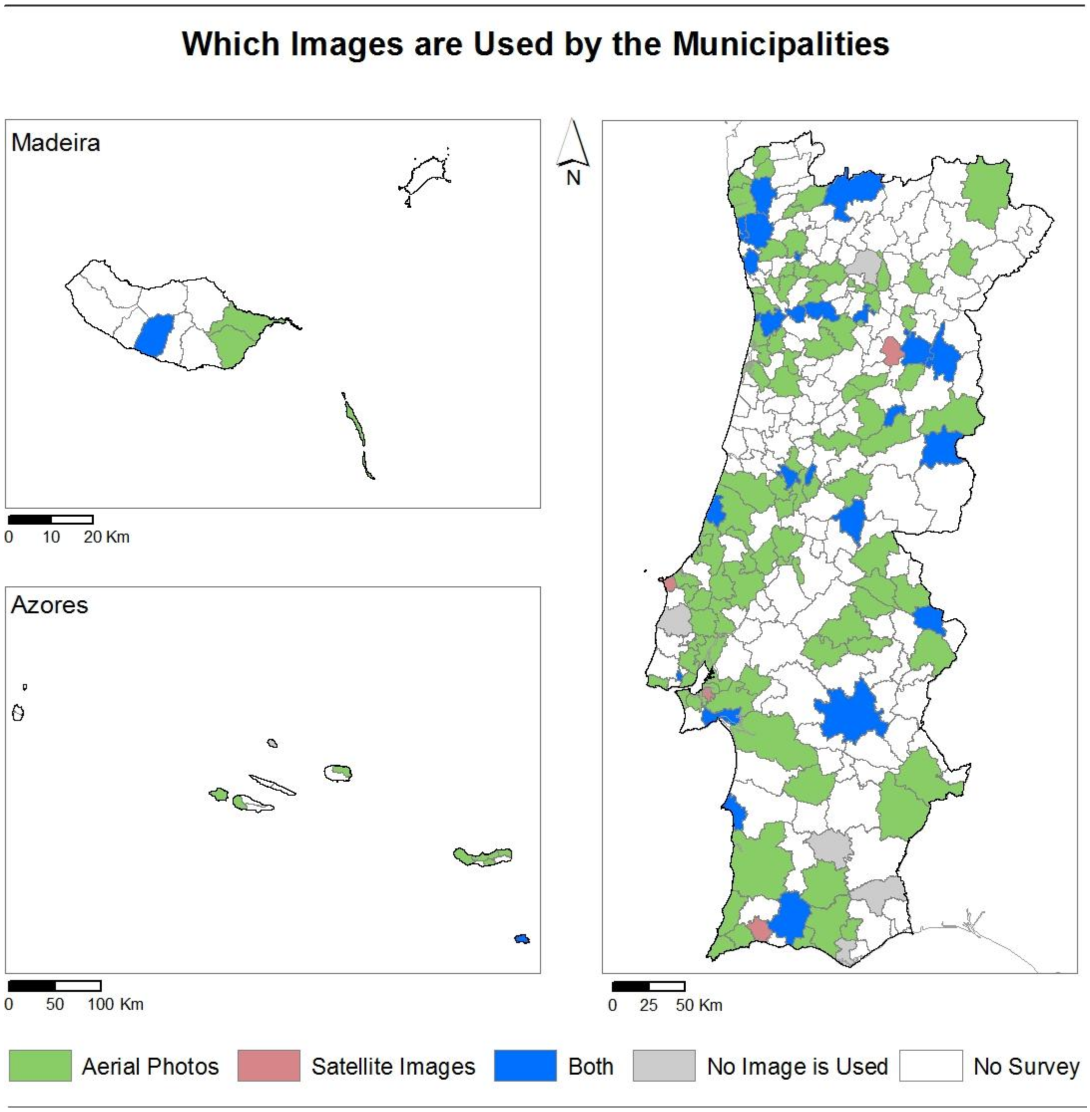


Figure 36. Types of images used by the Portuguese municipalities

When relating the type of VHR imagery and the operations in which GI is used, we conclude that aerial photography and satellite images are mainly used for GIS analysis.

Part 6 – Characterization of the GI used in the municipal activities

The first question in this group (question 6.1) addressed geographic elements already in use and the desired ones. Among the elements indicated in the questionnaire, Roads, Altimetry and Buildings, were indicated as the most used (86.4%, 86.4%, and 85.7% respectively), followed by Green area (68.6%) and Agricultural sites (64.3%). The most wanted elements were Trees (35.7%) and Children's parks (31.4%), followed by Buildings under construction (30.7%) (Table 10).

Table 10. Geographic elements used and required by the departments

Element	Use %	Want to use %	No reply %
Building	85.7	10.0	4.3
Building under construction	54.3	30.7	15.0
Swimming pool	50.0	25.7	24.3
Road	86.4	10.7	2.9
Parking lot	55.7	27.9	16.4
Children's Park	50.0	31.4	18.6
Green area	68.6	23.6	7.9
Tree	44.3	35.7	20.0
Agriculture site	64.3	22.1	13.6
Altimetry	86.4	10.0	3.6

Performing a cross analysis between the type of department and the most used elements, we found that GIS and Urbanism departments use mostly Buildings, Roads and Altimetry. The Environment departments use mainly Agriculture sites and Altimetry, Trees and Green areas, while Infrastructures use Buildings, Parking lots, Green areas and Altimetry. The other departments use Roads, Altimetry, Buildings and Green areas.

The most fundamental elements for the department's activities (question 6.2) were coincident with the most used: Buildings (75.7%), Roads (70.7%), Altimetry (62.1%) and Agricultural sites (33.6%). The elements considered irrelevant by the most part of the departments were Swimming pools (8.6%) and Trees (7.1%). On the open-ended section, elements like heritage landmarks, urban equipments, flood inundation maps, cadastral maps, hydrography, land use and land cover, were also pointed out as fundamental elements, already in use.

When relating the elements considered as fundamental (question 6.2) with operations they are used in (question 2.3), it was found that Buildings, Roads, Altimetry and Agricultural sites are mainly used in GIS analysis.

The question on the map scale (question 6.4) of the elements already in use, 1:2 000 was the scale most indicated for the Buildings (35.7%), followed by 1:10 000 (25.7%). The Roads are also most used at 1:2 000 scales (31.4%) and 1:1 000 (12.9%). The Altimetry is also most represented at 1:10 000 scales (30.7%), Green areas at 1:2

000 (32.9%), and the Agriculture sites at 1:10 000 (40.7%). On the desired map scale (question 6.5), all these elements are wanted by the departments at the 1:1 000 scale, except for the Agriculture sites, where 1:10 000 is the most selected scale.

On the frequency of update (question 6.6), Buildings require a monthly update frequency, the same for Roads, Green areas and Agriculture sites. Altimetry requires only an annual update (Table 11).

Table 11. Characterization of the map scale (in use and desired) and update frequency of the most used geographic elements

Element	Map Scale in use	Map Scale required	Update frequency
Buildings	1:2 000	1:1 000	Monthly
Roads	1:2 000	1:1 000	Monthly
Altimetry	1:10 000	1:1 000	Annually
Green areas	1:2 000	1:1 000	Monthly
Agriculture sites	1:10 000	1:10 000	Monthly

When relating the GI's main use (question 2.3) with the update frequency (question 6.6), it was found that higher update rates were requested when GI is used for analysis. When cartographic and visualization were the main purposes, lower periodicity was indicated.

The last question (question 6.7), asks for indicating the type of representation of the GI elements. Buildings, Green areas and the Agriculture sites are mostly represented as polygons, while Roads and Altimetry as lines.

5.3.5 DISCUSSION

The goal of the survey was to assess the use and value of GI for the Portuguese municipalities. After analyzing the responses provided by the departments, two conclusions regarding the survey arose. The first aspect is related with the ambiguity of the questions. In fact, there is no quantitative scale in some questions, but rather a qualitative one. In those situations, a range of values to characterize the response would be a good alternative (e.g., Very important in the scale of 0-5). Another aspect is related with the thoroughness within the municipalities. For a complete characterization, the most common departments that are present in the municipalities should have been consulted. However, this is a very demanding challenge since that universe is significantly more numerous than the number of municipalities, and would require a remarkable effort in order to select the appropriate departments is each municipality. Having stated this, and from a statistic point of view, the high response rate (45%) allows us to draw conclusions about the local government and the characteristics of the GI they use, with a margin of error of 5%.

Based on the survey results presented in the previous sections, it was found that every municipality that filled-in the questionnaire has GI in their departments. Except for one municipality in the Azores, all municipalities make use of the GI in their activities. Furthermore, besides using it, many departments also produce GI. The majority even pointed out that it is fundamental for their activities. These findings allow confirming that GI is in fact a valuable resource for the local government.

The next sections of the inquiry were to further investigate the attributes of the GI in use. From the survey results, we can conclude that GI is mostly used for analysis. Visualization and cartographic production are less important purposes.

The GI is obtained mainly from the own municipal and in other public services, giving the impression that the municipalities are comfortable and confident in their resources to manage the available GI and integrate it in their activities.

Another perception we wanted to confirm with the survey was the level of usage of images by the departments. Not surprisingly, aerial photographs are the most common type of images, and are used on a daily basis. However, satellite images were selected by 22.9% of the municipalities, and also a daily usage was indicated. Cost of image purchase and lack of informatics were indicated as the greatest obstacles to using this type of imagery. Once more, the images are mostly used in GIS analysis.

Concerning the geographic elements mostly used, Buildings, Roads, and Altimetry were the most indicated ones, followed by Green areas and Agriculture sites. This was already expected, since the questionnaires were mostly filled-in by Urban Planning departments.

Regarding GI representation, large scales are used for Buildings, Roads, and Green areas, but higher detail is desired by the departments. For the update frequency, only Altimetry was indicated as requiring an annual update. All other relevant elements require a monthly revision. Based on these responses we can conclude that GI is needed with higher spatial and temporal detail, in order to fulfill the departments' requirements on GI.

From this survey we can recognize two typologies of Portuguese municipalities based on their relation with GI. In the Type I, we can find municipalities that use GI produced by themselves for analytical purposes. This group demands a monthly update of its information. In Type II, we find municipalities where GI is obtained from outside their departments, and used mainly for visualization purposes. The required revisit frequency is, in this type, twice a year or annual. However, no spatial pattern was observed when characterizing these two types. Indeed, municipalities equally developed pointed similar aspects towards GI as less developed municipalities.

The generality of the survey responses reveal the technologic and structural assimetries existing in Portugal. In on side, we have municipalities with high penetration levels of information tecnologies, indepently of being GI related tecnologies. On the other side, we have municipalities where the technologic innovation arrives latter and with less amplitude. These situations are due to, 1) tradicional use of analog GI (namely by politions and middle managers) even when its acquisition is in and processing is conducted in adigital format; 2) the vertical structure of the public administration, that many times annuls the technicians's motivation through technologic innovation; and 3) the devaluation of GI due to the unawareness of its benefict in the decision-making process. These circumstances produce a great dissimilarity regarding the use of GI in Portugal.

Nevertheless, we can presume that GI is a fundamental resource for local government and calls for regular maintenance. Buildings were among the most frequently mentioned elements used by the departments, and therefore will be the focus of the next chapter (Chapter 6) where some case studies on GI collection and update will be presented.

6. GEOGRAPHIC INFORMATION FOR CARTOGRAPHIC AND ANALYTICAL APPLICATIONS

According to Goodchild (1997) geographic information is knowledge about *where* something is in the Earth's surface, and knowledge about *what* is at a given location. Geographic information is at the core of both cartography/mapping applications, and of spatial analysis within a GIS. The thematic, spatial and temporal characteristics of the mapped phenomena are determined by its final application, and data needed for inventory is different from data needed for spatial analysis. In this way, we can say that the cartographic objective is the optimal presentation of urban form (structures) and function with respect to the map purpose. More appropriately allied to spatial analysis, analytical geographic information makes use of the spatial representations which cartography produces in order to examine patterns, trends and make measurements in the data. Analysis transforms geospatial data into knowledge (ICA, 2010).

Users of geographic data on urban areas include departments in charge of planning, commerce, cadastre, transportation and traffic, recreation and tourism, environment, emergency, communication, private or public utility companies, private real estate companies, residential, commercial and industrial developers (SCOT-Conseil, 1997; Jensen and Cowen, 1999; Puissant and Weber, 2002). The municipalities are, in particular, responsible for physical planning and building control as well as the construction of most types of infrastructure (for example secondary and access roads, water, drainage and street lights) and, to a greater extent, the maintenance of related services. All these actions require geographic data, to produce large-scale maps (topographic maps) or to be used in less-scale dependent geospatial solutions.

Based on these facts, we suggest the use of VHR images in two distinct areas of application that require different levels of accuracy of geographical information. In fact, once the municipalities acquire a VHR image, it can be used in many ways, to maximize the return on the investment.

6.1. CARTOGRAPHIC APPLICATIONS

Map production has long been a core practice of cartography. Topographic map production based on geodetic, photogrammetric, remote sensing or laser scanning methods, is a part of the surveying process. In each country, topographic mapping has its own traditions and standards, including selection of the map projections and datum. In Portugal, in order for the cartography to be a legal document, it must comply with the technical specifications of the respective cartographic scale. If compliance is not met, the cartography is not homologated by the IGP. So, in cartographic applications, non-compliance with the specifications is a determinant factor, which can invalidate its final use.

The scientific literature on the use of VHR images data for mapping purposes suggests that this kind of images can be potentially used for feature extraction and large-scale cartographic updating. In 2003, the Ordnance Survey, Great Britain's national mapping agency, initiated a project to investigate the potential use of QuickBird imagery for updating maps at medium scale (1:25 000 and 1:50 000) and large scale (1:10 000 and larger) (Holland et al., 2006). Based of the visual analysis of the images, the authors concluded that QuickBird images were feasible to update topographic maps at scales between 1:6 000 and 1:10 000, if the mapping specification is modified to exclude small linear features such as fences and hedges. Gianinetto (2008) conducted some tests for updating the two Italian Technical Maps, one at 1:5 000 and the other at 1: 10 000. Results showed that the updating of the 1:10 000 scale was always possible, considering the Italian specifications, while a rigorous updating of 1:5 000 scale cartography was possible only in few situations.

Regarding the extraction of specific topographic features from VHR images, several tests on road networks (e.g., Mirnalinee, 2007; Zhang and Couloigner, 2006; Bacher and Mayer, 2005) and buildings detection (e.g., Ioannidis et al., 2009; Lefèvre et al., 2007; Mayunga et al., 2007) have been reported in the literature, but very few compare between the mapping accuracy that can be obtained from high-resolution satellite images and the actual requirements for large-scale mapping in well-mapped countries. Topan et al. (2009) compared a feature extraction from VHR images based on manual and automatic methods and concluded that only the information content of a 1:10 000 topographic maps could be derived from these images.

Freire et al. (2010) tested the building extraction from a QuickBird image of Lisbon, against a reference dataset, introducing cartographic constraints from scales 1:1 000, 1:5 000, and 1:10 000. Results showed that values for completeness varied with mapping scales and results were only slightly better for scale 1:10 000. Concerning the geometric quality, a large percentage of extracted features met the strict topographic standards of planimetric deviation for scale 1:10 000, while no buildings were compliant with the specification for scale 1:1 000.

A case study to document this type of geographic information application is presented in section 6.5.

6.2 ANALYTICAL APPLICATIONS

As already demonstrated in Chapter 5 (section 5.3.4), the municipalities use geographic information mainly for analysis. In fact geo-data can be used not only to produce maps, but also for supporting decision-making. Application fields like sustainability analysis using indicators, risk analysis and mapping, thematic mapping, geo-visualization or supporting the implementation of policies, all require geographic information. The emphasis is on the extraction of added value from the processing of spatial data on maps and the use of analysis and modeling techniques to support those activities.

Analytical cartography can be seen as the use of rational approaches to solving map-related problems in the real and virtual domain (Moellering, 2000). In this context, aspects related to large-scale mapping (e.g., at the building scale), such as high positional accuracies, are not so relevant since the goal is the characterization of a certain geographical phenomenon at the municipal level. In fact, when extracting information for these types of applications, compliance with the technical specifications of the respective map scale is not a requirement, and more effort is put in the thematic quality of the data. In this situation, unlike cartographic applications, the non-compliance with the scale's specifications, does not compromise the analytical purpose of the map. However, it is important to quantify the error present in the extracted geographic information, to allow computing the accuracy of the decisions based on it.

Three case studies to document this type of geographic information application are presented in sections 6.6, 6.7 and 6.8.

6.3 MULTI-DATA APPLICATIONS: FOUR CASE STUDIES IN THE CITY OF LISBON

This section presents four case studies where different types of high-resolution remotely sensed data can be used as a source of geographic information (GI) for municipal activities (Figure 37).

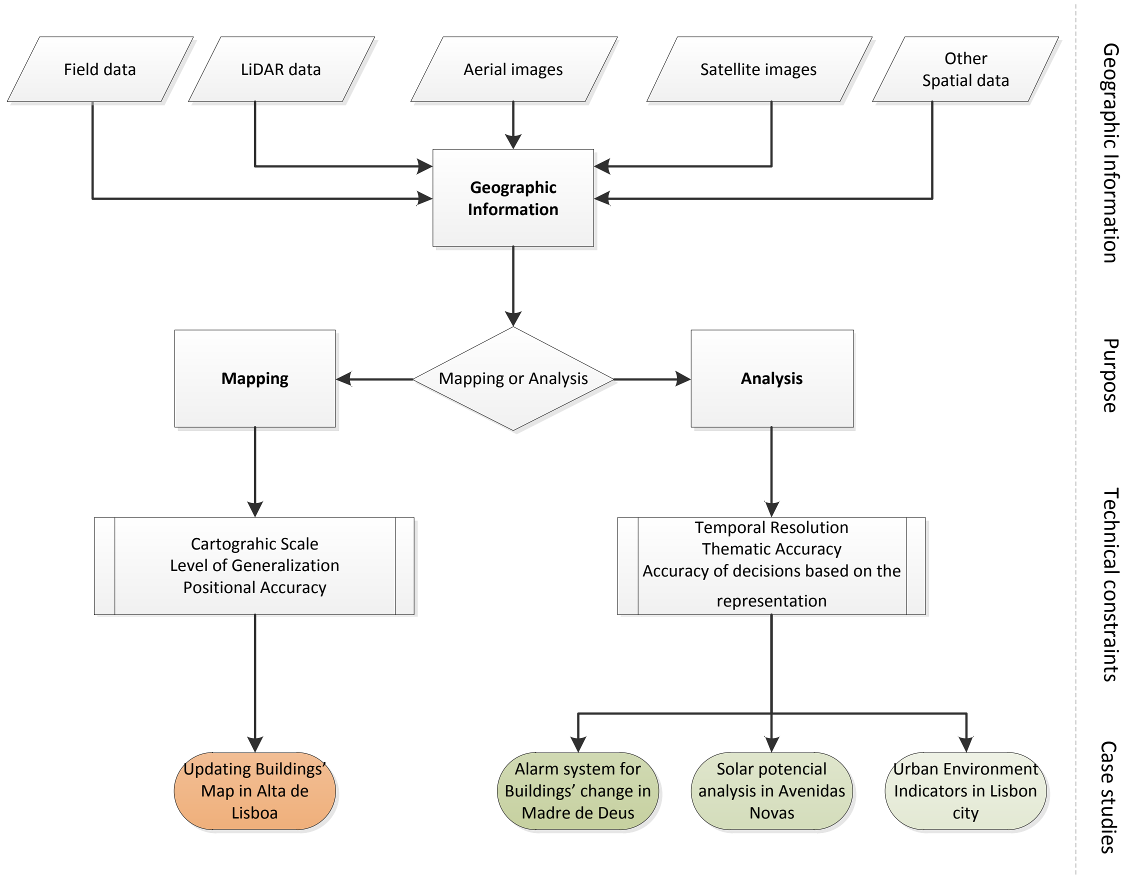


Figure 37. Case studies that illustrate mapping and analytical applications of geographic information

The first case study deals with updating large-scale cartography. This is one of the most demanding situations that require considerably human and technical resources, not always available in the municipalities. In this context, the information extracted from remotely sensed data is evaluated regarding the compliance with the technical specifications addressing the production of large-scale cartography.

The next three case studies deal with more analytical situations that also require GI. The second case is an application that explores the suitability of GI extracted from satellite data to be integrated in an alarm tool for pointing out potential changed areas. The third case consists in a methodology for evaluating the solar potential of a city's neighborhood, based on altimetric data. The motivation for this case study is the fact that incorporating solar systems into buildings, offers a mean to locally generate power, based in a renewable source of energy, the Sun. In this context, the use of LiDAR data can play an important role when analyzing the buildings capability for receiving the solar systems. Towards an indicator-based system, the cities' development can be monitored and steered. In the fourth case, the construction of indicators on municipal urban environment quality is presented, based on the exploration of optical and altimetric remotely sensed data.

6.3.1 Building's Map Updating Using Aerial Photography

Based on the survey presented in Chapter 5, we concluded that the municipalities require updated information mainly on "Buildings", "Roads" and "Altimetric data". Among these, buildings are the most relevant elements for the municipal activity, because there are administrative acts that occur on a daily basis that require updated information on these features. Situations like land subdivision into lots, redeveloped and/or extension of already existing buildings, emission of location maps for licensing acts or intervention on buildings, all require permission from the municipality. In order to grant such permissions, the municipal services need to have access to updated information on the land. Such land use information is also required for municipal tax administration. Therefore, the basis for all these activities depends heavily on the spatial information in the form of maps. Such detailed maps should be updated regularly.

To meet the requirements for updated data, we propose a methodology based on VHR imagery to detect and identify changes. An application using post-classification change detection methodology to detect new construction when updated cartographic data is unavailable is experimented in section 6.5. Such case study is a demonstration of situations where no cartography is available or it is not reliable. In those situations, the existence of two images from distinct periods enables the production of two land cover maps. A subsequent comparison assesses what changed between the two dates.

To evaluate the proposed methodology, a quality assessment must be carried out. To assess the quality of information extracted from images, based on the concept of reference value, it is necessary to assess levels of compliance with information from an independent source. This reference data can be obtained from a field survey (e.g. GPS collection), from an existing map having higher detail and accuracy, or from a map obtained by visual analysis and manual digitizing (Congalton and Green, 2009).

The nature of the images and their anticipated use require methods and metrics for assessing their adequacy which go beyond thematic accuracy alone. Indeed, the validation of large scale urban elements for GIS database purposes requires the identification of (1) feature class, (2) level of completeness and correctness, and (3) geometric quality of the elements (in line with existing standards) (Santos et al., 2009).

To assess the thematic quality, the area of overlap between classified and reference data is used. The area common to the two sets represents the thematic agreement and indicates the classification's Overall Accuracy. The area of reference polygons which have no correspondence in the classification stands for the Omission Error, while the area of polygons classified without representation in the reference stands for the Commission Error.

The completeness and correctness analysis are made using the centroids of the reference polygons and their intersection with the classification polygons. The geometric accuracy of the extracted information is evaluated using parameters, described in the mapping specifications, published by the IGP must be met (Table 12).

Table 12. Constraints for size and planimetric tolerance of features for selected scales of digital topographic data

Scales	**Area (m^2)**	**Tolerance (m)**	
		RMSE	90%
1:1 000	4	0.18	0.27
1:5 000	4	0.75	1.25
1:10 000	20	1.50	2.30

The goal is to test the methodology considering scales for maps frequently used at the municipal level. The assessment of geometric quality is based on the rationale that polygon area and shape are determined by its outline (enclosing line segments), so it makes sense to analyze the latter for deviation from a reference (Freire et al., 2010). However, this analysis is based on specifications that were conceived for estimating positional accuracy of point data. In this case study, those specifications were adapted to estimate the level of fitness between homologous polygonal features (reference and classified).

6.3.2 Alarm System For Land Use Land Cover Change in Urban Areas

When cartographic information exists, but is out-dated, a change detection procedure using recent geographic data can be applied for map updating. The aim of this analysis is to highlight those areas where changes most likely have occurred. This new product, in a first stage, can be analyzed by municipal technicians that will: (1) decide, based on analysis of the image and related information, if the marked spot is in fact a changed area (a new urbanization or a built-up object that was demolished), and if so, (2) digitize the new buildings into the old cartography, or eliminate them, thus producing an updated map, if the *alarm layer* is accurate enough, or send a topographer to verify it directly in the field. If the spot is considered to be a false detection, than the technician will (3) eliminate it.

All these actions can be done using a GIS interface where the most recent building map is overlaid over the high-spatial resolution imagery, and where attributes like ongoing urban processes or the Constraints Master Plan, can also be seen. In this environment, any municipal department can query a complete, citywide representation of property boundaries and, by zooming in or out, see spatially the new corrected property lines.

In a second step, additional data sources must be used in order to further add attributes which cannot be detected in the imagery, like street names, land use type or ownership information. Such methodology can be used by the municipality to keep its cartographic database of urban areas up-to-date between two aerial photographic campaigns.

To overcome the problem of outdated data, a methodology based on VHR imagery and LiDAR data to detect and identify changes is proposed. The usage of more recent geographic data in order to update already existing cartography is tested in section 6.6.

6.3.3 Mapping Buildings' Solar Potential

Portugal, as a member of the EU, has to implement the Energy Performance of Buildings Directive which requires all EU countries to enhance their building regulations and to introduce energy certification schemes for buildings. Energy Performance Building Regulation is already implemented in Portugal since April 2006, and requires, among others, a minimum contribution from solar thermal systems based on the type and size of the building. The 2001/77/CE Directive defined for Portugal, a target of 39% of the consumed electricity to originate from renewable energy sources. This objective was increased to 45% for 2010. The transposition of the CE Directive encompasses Regulation on Energy and Acclimatization Systems in Buildings and Regulation on the Thermal Performance of Buildings. This legislation imposes the installation of solar panels on new buildings, therefore making it possible to effectively reduce energy consumption in this sector. This new awareness, associated with the fact that Portugal is one of the European countries with the highest levels of annual solar radiation (Šúri et al., 2007), contributes to a growing interest in the quantification of energy-based indicators at the city and building's scale, in order to assess photovoltaic conversion and thermal solar potential.

Identifying buildings that are suitable for solar panel installation then requires modeling two variables: 1) the solar radiation incident in each location and, 2) the optimal location for the panels on the roof.

Solar radiation, incident on the Earth's surface, is a result of complex interactions of energy between the atmosphere and surface. These interactions are determined by three groups of factors (Hofierka and Šúri, 2002):

- The Earth's geometry, revolution and rotation (declination, latitude, solar hour angle) - this group of factors determines the available extraterrestrial radiation based on solar position above the horizon and can be precisely calculated using astronomic formulas;
- Terrain (elevation, surface slope and orientation, shadows) - the radiation input to the Earth's surface is then modified by its terrain topography, namely slope inclination and aspect, as well as shadowing effects of neighboring terrain features. This group of factors can be also modeled at a high level of accuracy;
- Atmospheric attenuation (scattering, absorption) by gases (air molecules, ozone, CO_2 and O_2), solid and liquid particles (aerosols, including non-condensed water), and clouds (condensed water) - because of its dynamic nature and complex interactions this factor can be modeled only at a certain level of accuracy that decreases from gases to clouds.

The incident solar radiation can be measured by ground-based meteorological stations or meteorological satellites, or be estimated through models. There are several solar models available in the literature. They vary in the detail of the input parameters and, consequently, in the output map. Solar Analyst and Photovoltaic Geographical Information System (PVGIS), are two examples of solar radiation models.

The Solar Analyst module in ArcGIS can be used to calculate Watt-Hours/meter^2 at the surface and at the local scale (Fu and Rich, 1999). Inputs to this process are a digital elevation model, the latitude of the scene centre, the sky size, and the date and time one wishes to accumulate insolation and radiation parameters such as Transmittivity and Diffuse proportion. Therefore, the model accounts for atmospheric effects, as well as site latitude and elevation, steepness (slope) and compass direction (aspect), daily and seasonal shifts of the Sun angle, and effects of shadows cast by surrounding topography.

The PVGIS, developed by the JRC, allows users to estimate solar energy performance at any given location. PVGIS developed a GIS-based methodology for computation of solar irradiance/irradiation at a given surface inclination for any geographical region and for any time moment or interval. This approach has been implemented in the GIS software GRASS and it is based on use of the solar radiation model *r.Sun*, and the spatial interpolation techniques *s.surf.rst* and *s.vol.rst*. For each time step during the day the computation accounts for sky obstruction (shadowing) by local terrain features (hills or mountains), calculated from the digital elevation model. This model is a grid with 1 km resolution, derived from the USGS Shuttle Radar Topography Mission (SRTM) data. PVGIS provides a solar radiation database for the European Subcontinent, the Mediterranean Basin, Africa and South-West Asia. The modeling accuracy of the PVGIS values in the database was evaluated against the input meteorological data used in the computation. Comparing the yearly averages of the daily global horizontal irradiation, the mean bias error is 8.9 Wh/m^2 (0.3%) and the RMSE is 118 Wh/m^2 (3.7%) (JRC, 2010).

Regarding the panels' optimal location stage, manipulating LiDAR data within a GIS is a straightforward way of identifying appropriate roof areas. Applying algorithms to automatically classify and segment LiDAR data, enables analyzing buildings' roofs according to their slope, azimuth, and shaded areas.

Knowing the amount of incident solar radiance, and the optimal roof areas for capturing that energy, the solar potential of any roof plane can be easily calculated (e.g., Vögtle et al., 2005; Rottensteiner et al., 2005, Kassner et al., 2008; Izquierdo et al., 2008; Jochem et al., 2009; Hofierka and Kaňuk, 2009; Wiginton et al., 2010). The potential can be evaluated regarding electricity production (photovoltaic solar panels), or water heating capabilities (thermal solar panels). The knowledge of solar accessibility on urban surfaces, allows investigating the energy-performance of cities, namely the environment and the economic impact of using solar energy. On the environmental side, factors like absence of pollution or generation of greenhouse gases can be evaluated (Alsema, 2000; Reich et al., 2007). On the economic potential of solar panels, analyzing factors like the payback period based on current prices, gives the expected cost of the energy produced by the solar energy system, averaged over the lifetime of the system (e.g., Pillai and Banerjee, 2007; Gomes, 2011).

The use of solar models and LiDAR data in order to produce a map with the solar potential at the roof tops is tested in section 6.7.

6.3.4 Urban Environmental Indicators

Cities are complex and dynamic systems that reproduce the interactions between socio-economic and environmental processes at a local and global scale. The synchronism and coexistence of economic activities, environmental threats, infrastructural deficits, poverty and population growth mark a significant challenge to urban planning. Integrating and correlating multiple analysis tools (image analysis, GIS), data types (satellite images, vector data or statistics) and data sources (EO, survey or census) is an important step towards the increase of information content quality and its acceptance by decision makers (Esch, 2010). Systems based on different urban indicators can be used as tools for cities to communicate different environmental risks, and promote strategies and measures of sustainable urban development and disaster risk management. Monitoring indicators of key processes in land use and economic development is essential for evaluating policy measures. A variety of methods and systems are available to monitor the quantity and quality of natural resources.

An **environmental indicator** is usually defined as a number indicating the state and development of the environment or conditions affecting the environment (Alfsen and Sæbø, 1993). The territory is, structurally and dynamically, a complex system that requires the use of observation tools to support the local government (Sède-Marceau and Moine, 2008). Beyond the provision of raw data, the indicators design seems like a privileged tool to transmit synthetic information and to evaluate actions (caENTI, 2007). The indicators concern several different logics, describing either the state of the system (diagnosis), or the impact on installation policies (evaluation), or possible system evolutions (futurology) (Sède-Marceau and Moine, 2008). An indicator system then can enable the perception of the heterogeneity and the spatial variable of the phenomena within the territory. This ability can simply be acquired by means of simple cartographic approaches based on putting thematic data in a certain spatial context. But it might also be necessary to develop more complex indicators, providing information about the shape, the structure and the organization of phenomena (Joerin et al., 2001).

One obvious source of information about the urban environment is remote sensing data. The constantly increasing availability and accessibility of modern remote sensing technologies has provided new opportunities for a wide range of urban applications such as mapping and monitoring of the urban environment (land cover, land use, morphology, urban structural types), socio-economic estimations (population density), characterization of urban climate (microclimate, human health conditions), analysis of regional and global impacts – (ground water and climate modeling, urban heat islands) or urban security and emergency preparedness (sustainability, vulnerability) (Esch, 2010).

After collecting data on land cover from remote sensing data, several indicators can be assessed. Indicators on land sealing area, quantification of green area, or the vacant land available in the city, are ecological measures that can be used for monitoring and analyzing trends over the territory. Studies on impacts of urbanization, responses to natural and man-made disasters, vulnerability analysis or housing conditions, all require land-based indicators. The geographical data constitute the base of the spatial representation of the indicators. Urban indicators are designed to measure the quality of life and the nature of development of an urban area. These indicators can be used to make policy and planning decisions, to identify whether policy goals and targets are being met, and sometimes to predict change.

The usage of VHR imagery and LiDAR data in order to produce a land cover map, from which environment indicators are assessed for the city-scale, is tested in section 6.8.

6.4 DATA SETS AND PRE-PROCESSING

The data explored in the case studies are of three types: planimetric, altimetric and spectral. All data were pre-processed in their original extent and then extracted for the respective study area of each case study.

6.4.1 DATA SETS

Planimetry

The planimetric information corresponds to the Lisbon's Municipal Cartography (Carto98). This map, from the Lisbon City Hall, was produced in a vector format, for the year 1998, and has a scale of 1:1 000. It is a topographic map that describes the city in large detail through 50 themes, from "Buildings" to "Hydrography", to "Agriculture" and "Water Infrastructures", among many others. It is available in digital format.

Altimetry

The altimetric data is composed by two sets. One set is derived from a LiDAR (Light Detection And Ranging) point cloud, and the other is derived from cartography. From a flight with a LiDAR camera performed in 2006, a surface image was produced based on the 2^{nd} return, with 1 m resolution. This image represents the Digital Surface Model (DSM) of the area. Another source of altimetric information was a set of elevation mass points and contours, retrieved from 1:1000 scale altimetric cartography of 1998.

Spectral data

Two types of spectral data are available for the city of Lisbon: airborne and satellite images.

The orthophotos from 1998 were originally obtained in analogical format and then scanned to a digital format with the three visible bands and a 40 cm pixel size. The orthophotos from 2004 were obtained with a digital camera that recorded in the three visible bands (RGB) plus the near infrared. The 2004 image has a 50 cm pixel size and a higher quality than the 1998 image.

The satellite data comprises two images: a QuickBird and an IKONOS image. The QuickBird image was acquired in April 14, 2005. The image has a spatial resolution of 2.4 m in the multispectral mode (visible and near-infrared bands), a pixel size of 0.6 m in the panchromatic mode, and a radiometric resolution of 11 bits. The image was recorded with an off-Nadir angle of 12.2º. The sun azimuth and elevation of the image are 149°.6 and 57°.3, respectively and the satellite azimuth is 115.2º. The IKONOS image was acquired in June, 30, 2008, and has a spatial resolution of 4 m in the multispectral mode and 1 m in the panchromatic mode. The Lisbon city area was captured in four images, which were then mosaic into a single large image.

Table 13 summarizes the original characteristics of the planimetric, spectral and altimetric data set selected.

Table 13. Original characteristics of the data set explored in the case studies

Data type	Name	Date	Spatial resolution/ scale	Spectral resolution	Radiometric resolution
Planimetric	Municipal Cartography	1998	1: 1000	-	na
Altimetric	Elevation points and contours	1998	1: 1000	-	na
	DSM	2006	1 m	-	32 bit
Spectral	QuickBird	2005	MS 2.4 m Pan 0.60 m	Red, Green, Blue, NIR	11 bit
	IKONOS-2	2008	MS 4 m Pan 1 m	Red, Green, Blue, NIR	11 bit
	Orthophoto	1998	0.40 m	Red, Green, Blue	8 bit
	Orthophoto	2004	0.50 m	Red, Green, Blue, NIR	8 bit

na – not available

6.4.2 DATA PRE-PROCESSING

The pre-processing stage included several operations with the goal of geometrically correcting the data sets and to derive additional information for land cover and land use characterization (the DTM, the nDSM and the NDVI image).

Planimetry

The Municipal Cartography was geo-referenced. The map, originally in the datum 73 system, was re-projected to the PT-TM06/ETRS89 coordinate system. No further pre-processing actions took place. Figure 38 shows the map for the whole Municipality of Lisbon.

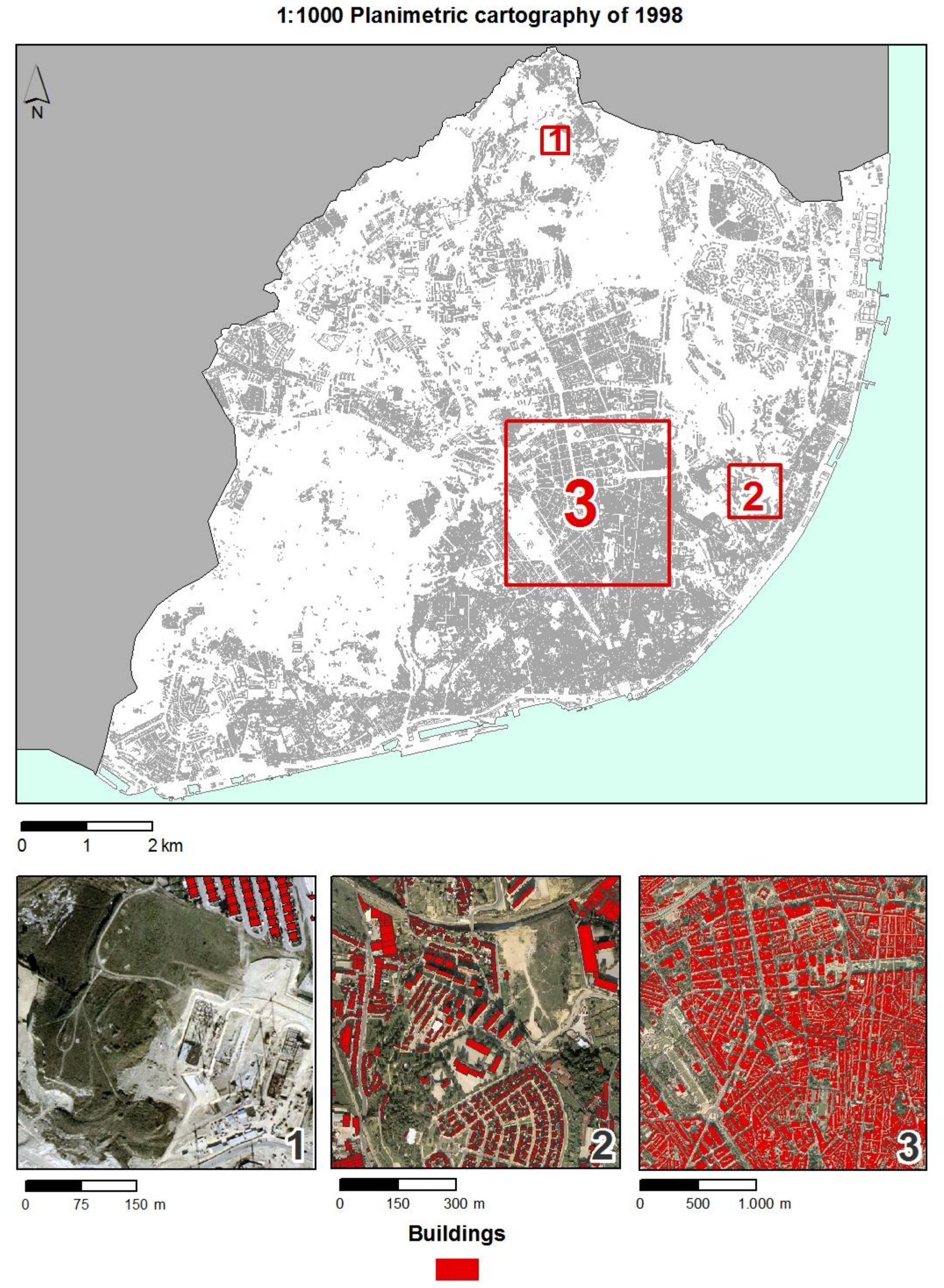


Figure 38. 1:1000 Planimetric cartography of 1998, for Lisbon

Altimetry

The altimetric data suffered several operations in order to generate the final maps describing the terrain and the surface.

A Digital Terrain Model (DTM) for the city of Lisbon was produced from the elevation mass points and contours. Firstly, a Triangulated Irregular Network (TIN) was generated and then converted to a grid with 1 m of resolution. This final file corresponds to the DTM for the area.

The DTM was then used to orthorectify the QuickBird image, and to derive the normalized Digital Surface Model (nDSM).

The nDSM was obtained by subtracting the DTM from the DSM image. This raster file stores the height of all elements above and below the terrain (Figure 39). The height values were not post-processed, meaning that false negative values are present in the dataset. These false values are mainly located in lakes and rail overpasses (locations where the railway crosses over the road). These effects result from the fact that the DTM is not as accurate and detailed as the LiDAR DSM in such situations. In fact, such circumstances (e.g., bridges, tunnels, overpasses), require further processing in order to correctly model the terrain by introducing break lines that reflect abrupt changes in the terrain and control surface behavior by acting as a barrier to the interpolation of the TIN model (Pfeifer, 2005). Since our DTM was first produced for the whole city of Lisbon, and only then the study areas were extracted, such situations are likely to appear, since they were not controlled. Nevertheless, these situations are identified in the city's area and do not affect the feature extraction process. Another factor that contributes to incorrect height values is the time lag between the DTM (1998) and the DSM files (2006). Some negative values are in fact due to terrain modifications (e.g., excavation activities) between both dates.

All files were geometrically corrected to attribute a common coordinate system (PT-TM06/ETRS89). The nDSM and the planimetry were well registered after this stage.

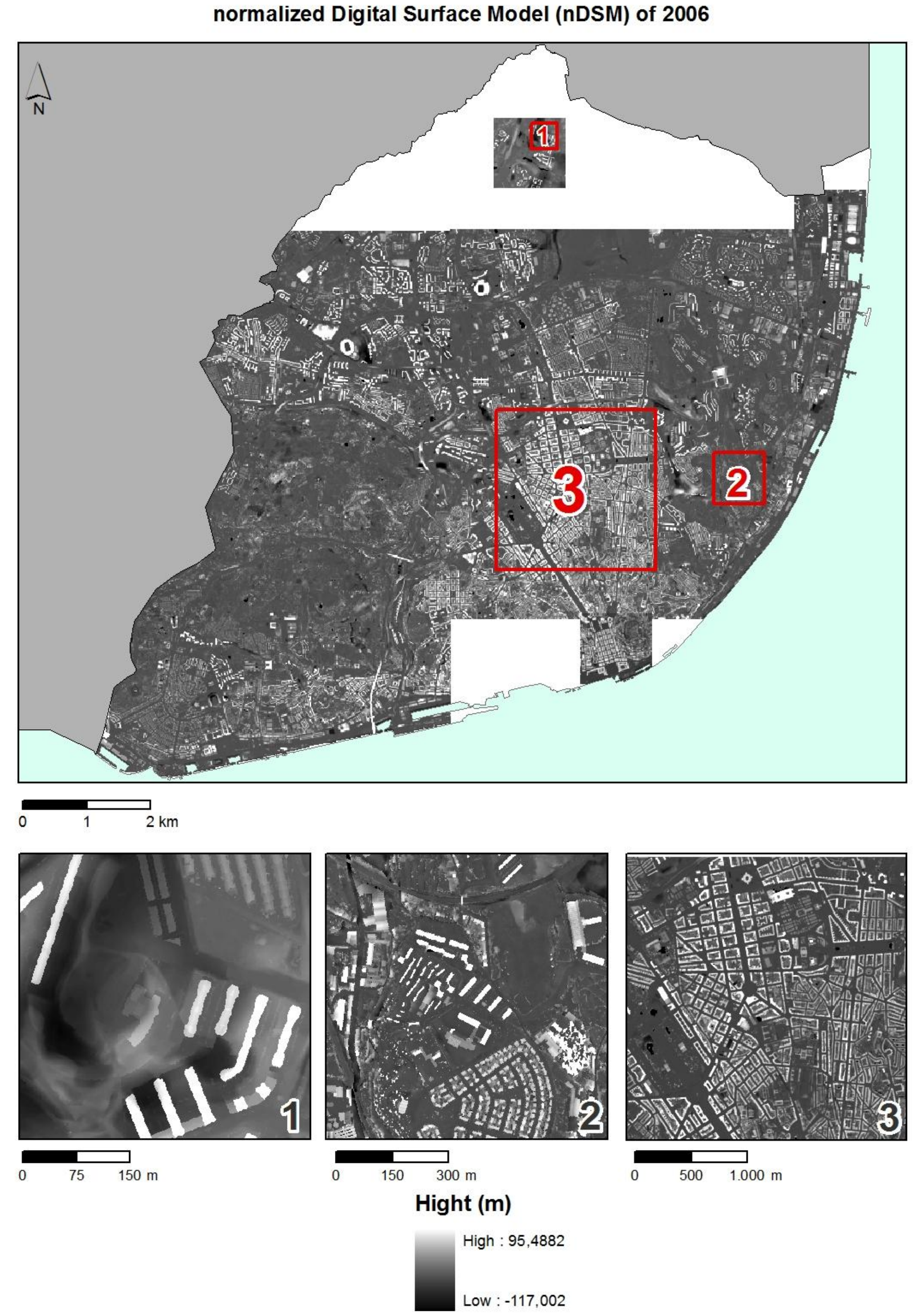


Figure 39. normalized Digital Surface Model (nDSM) produced with the altimetric data

Spectral data

The spectral data set were geo-referenced and co-registered. The **QuickBird** imagery was orthorectified in order to reduce the geometric distortions introduced by the terrain and to attribute a national coordinate system (PT-TM06/ETRS89). Previously, a pansharp image fusing the multispectral and panchromatic bands was produced for visual benefit, using the method available at PCI Geomatica. The orthorectification of the multispectral, pan, and pansharp images was performed based on the RPCs, available with the image, and a set of 36 ground control points retrieved from the 1:1 000 planimetric and altimetric cartography of 1998, available from the Lisbon City Hall. For the elevation reference, the DTM, retrieved from 1:1 000 cartography as described above, was applied. A 2nd order polynomial was selected for the transformation. To evaluate the process, 40 check points, well distributed across the image, were used. The obtained RMSE was less than one pixel (Table 14). Afterwards, a NDVI image was produced to integrate the dataset for feature extraction.

Table 14. The residuals in control and check points of QuickBird's orthorectification

Nº	Type of point	Image	Residual $_X$ (m)	Residual $_Y$ (m)	RMSE (m)	Pixel size (m)
36	Ground Control Points	Multispectral	1.21	1.05	1.60	2.40
		Pan	0.32	0.33	0.46	0.60
		Pansharp	0.32	0.33	0.46	0.60
40	Check Points	Multispectral	0.71	0.80	1.07	2.40
		Pan	0.35	0.35	0.49	0.60
		Pansharp	0.35	0.35	0.49	0.60

The QuickBird's off-Nadir angle of 12.2º was responsible for the imperfect registration between the imagery and the altimetric and planimetric data set (Figure 40).

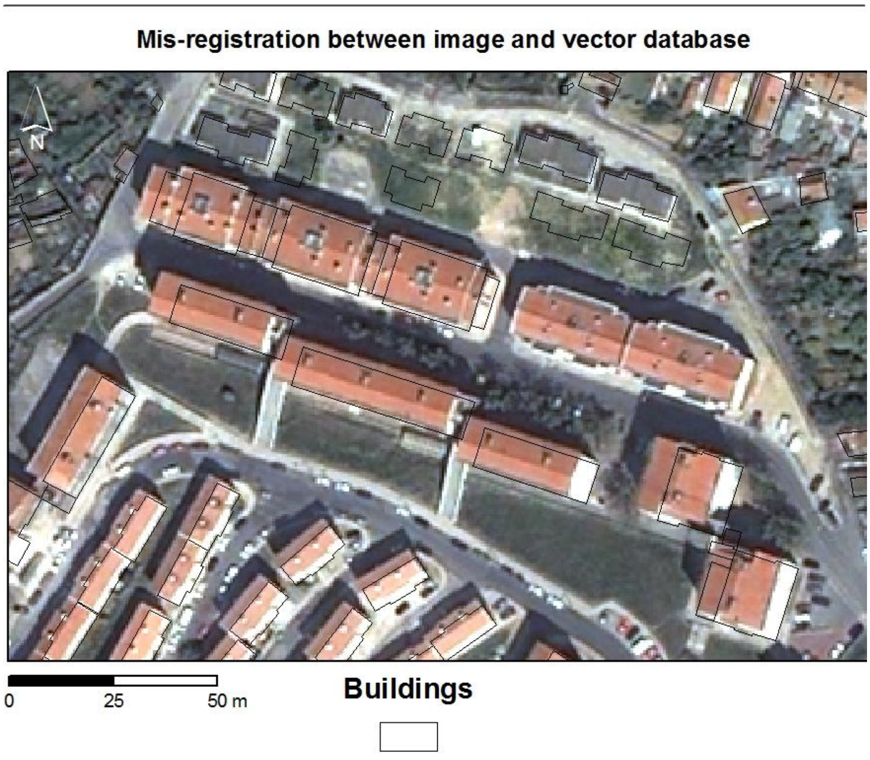


Figure 40. Registration problems between QuickBird imagery and the 1:1000 planimetry

The **IKONOS** image was also orthorectified using the same process as the QuickBird. It was based on the RPCs and 48 ground control points retrieved from the 1:1 000 planimetry. Furthermore, 55 check points were selected to evaluate the transformation. The obtained RMSE was less than one pixel (Table 15). Afterwards, a Normalized Difference Vegetation Index (NDVI) image was produced to integrate the dataset for feature extraction.

Table 15. The residuals in control and check points of IKONOS' orthorectification

Nº	Type of point	Image	Residual $_X$ (m)	Residual $_Y$ (m)	RMSE (m)	Pixel size (m)
48	Ground Control Points	Multispectral	0.52	0.71	0.88	4
		Pan	0.38	0.46	0.60	1
		Pansharp	0.35	0.45	0.57	1
55	Check Points	Multispectral	1.22	1.44	1.89	4
		Pan	0.55	0.53	0.76	1
		Pansharp	0.51	0.51	0.72	1

Besides satellite images, the explored spectral data set also included two **orthophotos**. Both sets of orthophotos were already projected in the same coordinate system, the Datum 73. However, the spatial resolution was different. The 2004 orthophoto was selected as the reference data and the pre-processing included the geometric registration of the 1998 orthophoto to the 2004 and consequent resample of its pixel to 50 cm.

Table 16 shows the characteristics of the data set used in the following sections, after pre-processing.

Table 16. Characteristics of the data set, after pre-processing, explored in the case studies

Data type	**Name**	**Date**	**Spatial resolution/ scale**	**Reference System**
Planimetric	Municipal cartography	1998	1: 1000	Projection: Transverse Mercator Ellipsoid: GRS80 Planim. Datum: ETRS89 Altim. Datum: Marégrafo de Cascais
Altimetric	DTM	1998	1 m	
	DSM	2006	1 m	
	nDSM	2006	1 m	
Spectral	IKONOS	2008	4 m/ 1 m	
	NDVI	2008	1 m	
	QuickBird	2005	2.4 m/ 0.60 m	
	NDVI	2005	2.4 m	
	Orthophoto	1998	0.50 m	Projection: Gauss-Krüger Ellipsoid: Hayford Planim. Datum: Datum73 Altim. Datum: Marégrafo de Cascais
	Orthophoto	2004	0.50 m	

6.5 BUILDING'S MAP UPDATING USING AERIAL PHOTOGRAPHY

A post classification strategy was applied in a study area located in the northern part of Lisbon, using orthophotos from two time periods. No other data was explored in this case. The goal was to produce two land cover maps, from different periods, using a feature extraction based methodology. The objective was then to analyze the changes between the two maps, in a post-comparison analysis.

The evaluation occurred in three steps: first, the change was detected (yes/no analysis), then its nature was assessed in terms of the classes that transitioned from on land cover class to another (from-to analysis) and, finally, it was quantified in terms of the area.

The class "Buildings" was subjected to a change detection accuracy assessment to allow calculating quality indices for the applied methodology.

This case study demonstrates the possibility of producing land cover maps and conduct change detection analysis in those situations where no cartography, current or historic, is available, but VHR optical images are.

6.5.1 STUDY AREA AND DATA SET

The area selected to experiment the post classification change detection approach was located in the Alta de Lisboa. The study area occupies 16 ha (400 m X 400 m), and provides a good example of very dynamic land cover changes occurring in the last decade in the municipality of Lisbon (Figure 41). The area comprises herbaceous vegetation, shrubland, bare soil, single-family housing (in 1998) and multi-family apartments (in 2004), schools (in 2004) and roads.

The classification was performed on the orthophotos from 1998 and 2004. In both dates, a principal component analysis was applied in order to allow a better identification of the buildings. In 1998, the buildings were best detected by the second principal component, while in 2004 that occurred in the third component. These principal components were included in the respective spectral dataset to be classified.

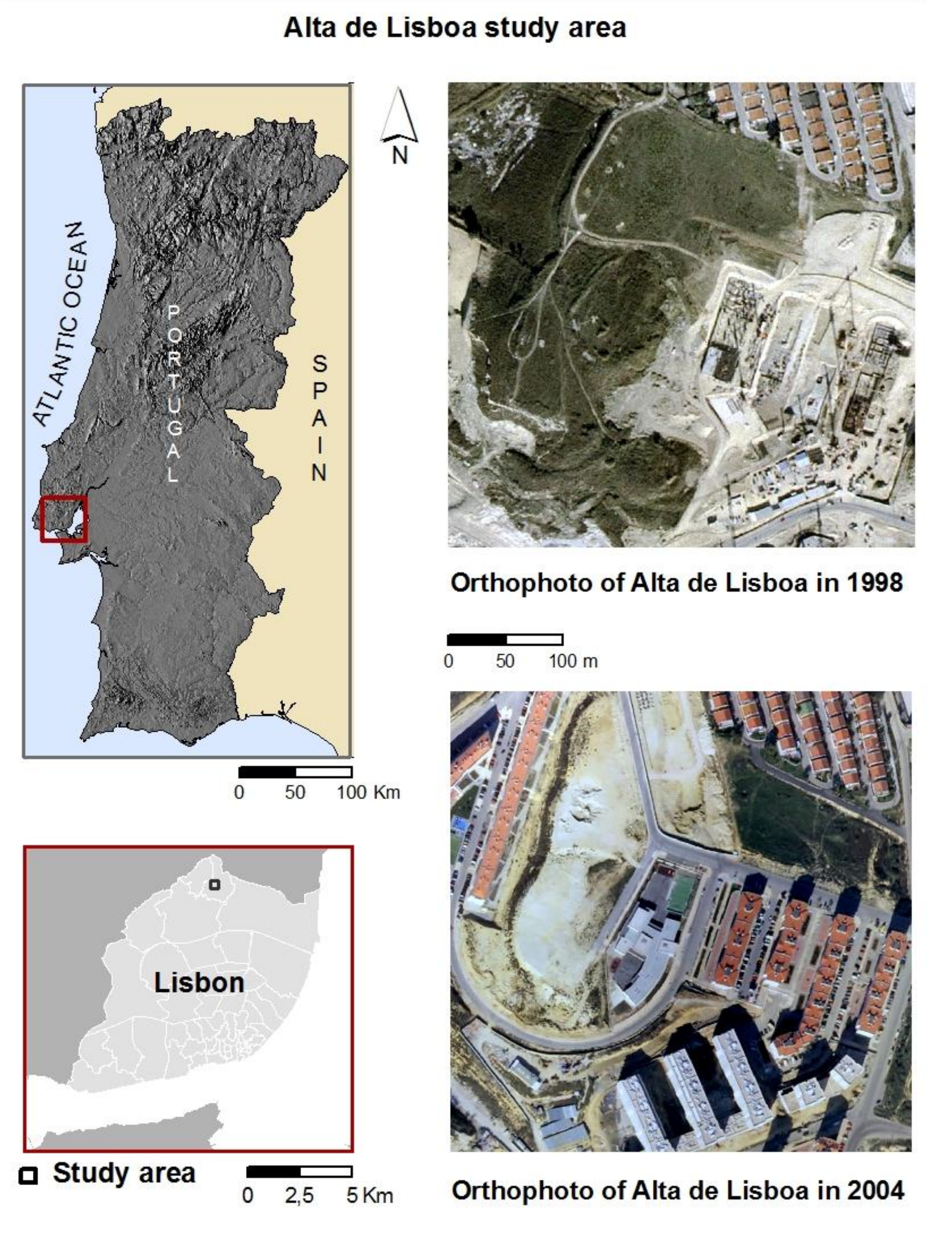


Figure 41. Location of the study area and the orthophotos from 1998 and 2004 used for change detection

6.5.2 LAND COVER CLASSIFICATION

Because the study area changed so dramatically between the two periods under analysis – 1998 and 2004 – a land cover nomenclature similar for both dates was difficult to implement. Therefore, slightly different two-level land cover nomenclatures were developed to classify each date (Table 17 and Table 18). In the first level, the nomenclature identifies four major land cover classes. The "Building" class includes permanent structures that have a roof and walls, and that have an area greater than 50 m^2. This class comprises uni and plural-family housing, annexes, commercial and industrial complexes, and administrative/public utilities. The “Bare soil” class identifies those areas of rocks, thin soil or sand. Transitional areas like construction sites are also included in this category. The “Pavement” class includes impermeable areas like roads, parking lots, concrete or asphalt surfaces, and sidewalks. The “Vegetation” class consists of herbaceous, shrubs, and trees.

Table 17. Land cover nomenclature for 1998

Land cover classes in 1998	
Level 1	**Level 2**
Building	Building with orange tile
	Building with other roof
Bare soil	Bare soil
Pavement	Roads
	Sidewalks and other impermeable surfaces
Vegetation	Shrubs

Table 18. Land cover nomenclature for 2004

Land cover classes in 2004	
Level 1	**Level 2**
Building	Building with orange tile
	Building with fibrocement
	Building with dark tile
	Building with other cover
	Building’s façade*
Bare soil	Bare soil
Pavement	Roads
	Sidewalks and other impermeable surfaces
Vegetation	Shrubs
	Herbaceous vegetation
Shadow	Shadow*

The 2004 classes “Shadow” and “Building’s façade” were used here as auxiliary classes since they are not valid land cover classes to be analyzed in the change detection process.

The land cover extraction was conducted in ArcGIS 9.3 (ESRI), using Feature Analyst 4.2 (Visual Learning Systems, Inc.) for ArcGIS. Feature Analyst allows classifying and extracting only the features belonging to the class of interest. The first step was the identification of training areas for each class. This was done by visual analysis of the orthophotos, supported by auxiliary information like the oblique images available at www.bing.com/maps, and field work done in 2008. The second step was the definition of classification parameters such as the number of bands to be classified, the use of histogram stretch, the resample factor, the input representation and pattern width, masking, and learning options like the learning algorithm or the level of aggregation.

The extractions were conducted independently for each class at a time in each image date and the methodology applied was similar. For all classifications a resampling factor of 1 (no resampling) and a histogram stretch were used, as well as the approach 1 for the learning algorithm and the 'find rotated instances of features' option. The parameters selected in the Feature Analyst to train the classifier are described in Table 19 and Table 20.

Table 19. Parameters used for training the classifier to extract features in the 1998 image

Level 2 classes	**Training areas**	**Representation and width**	**Aggregation (pixels)**
Building with orange tile	4	Manhattan 5	100
Building with other roof	1	Manhattan 5	100
Bare soil	8	Manhattan 5	1000
Roads	5	Bull's Eye 2 7	200
Vegetation	4	Manhattan 3	100
Sidewalks and other impermeable surfaces		Remaining area	

Table 20. Parameters used for training the classifier to extract features in the 2004 image

Level 2 classes	**Training areas**	**Representation and width**	**Aggregation (pixels)**
Building with orange tile	8	Manhattan 5	200
Building with fibrocement	5	Manhattan 5	300
Building with dark tile	8	Manhattan 5	100
Building with other cover	3	Manhattan 5	300
Building's façade	2	Manhattan 5	100
Bare soil	16	Manhattan 5	1000
Roads	11	Bull's Eye 2 7	200
Shrubs	9	Manhattan 3	50
Herbaceous	17	Bull's Eye 2 11	100
Shadows	15	Manhattan 3	100
Sidewalks and other impermeable surfaces		Remaining area	

After the initial classification, the maps were improved using the 'removing clutter' or 'adding missed features' tools. The Level 1 maps obtained from the feature-based classification of Alta de Lisboa in 1998 and 2004 are displayed in Figure 42. In the 2004 map, we can see that new buildings could not be well individualized. In those situations, only the building block could be extracted.

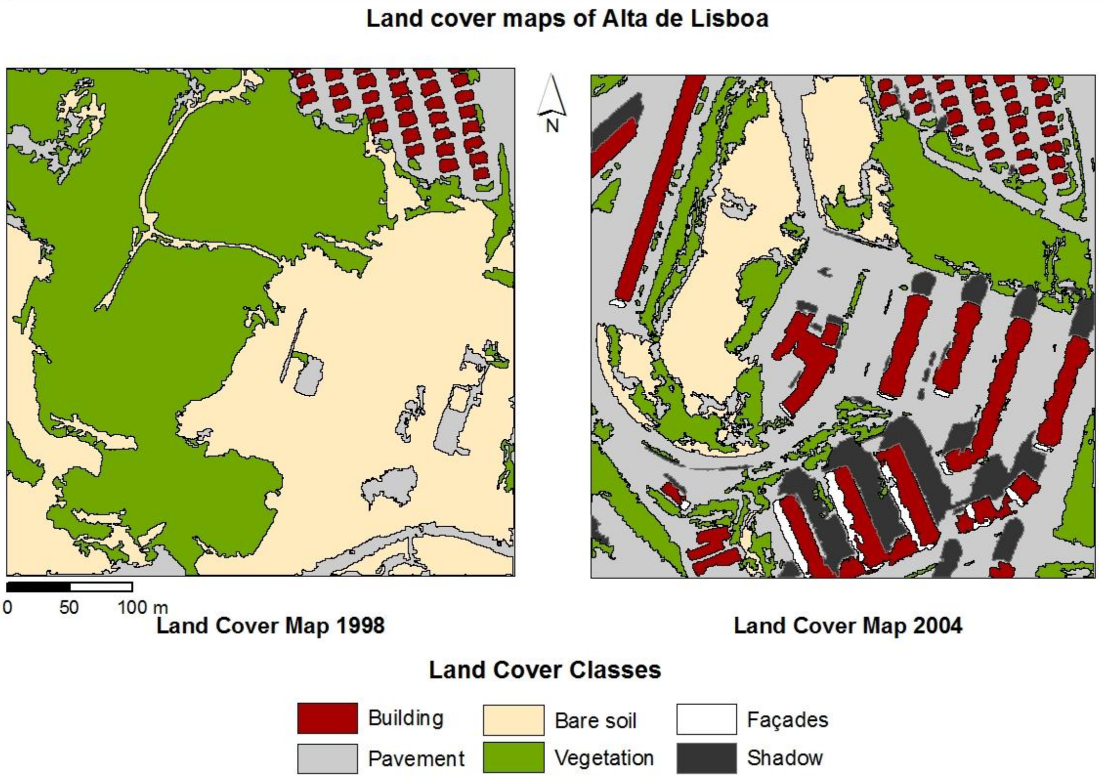


Figure 42. Land cover maps of Alta de Lisboa, in 1998 and 2004 obtain with FA

6.5.3 Land Cover Change Detection

Multi-date feature-based post-classification change detection was performed to investigate land cover dynamics in the study area from 1998 to 2004, following the land cover classifications for the two years. This technique allows quantifying not only change and no-change areas, but also the inter-class changes ("from-to"). The principal advantage of post-classification comparison is the fact that the two dates of imagery are classified separately, thereby minimizing the problem of radiometric calibration between dates (Coppin et al., 2004). Note that the 2004 classes "Shadows" and "Façades" are not considered in this change analysis evaluation, therefore the respective areas (13862 m^2) are subtracted from the overall study area (160 000 m^2).

Table 21 lists the area and proportion of each of the four land cover classes for the study area in 1999 and 2004. The changes of the area and percentage for each of the four classes from 1998 to 2004 were also summarized in Table 21. The table shows that the areas of “Bare soil” and “Vegetation” were greatly reduced, whereas the areas of “Building” and “Pavement” increased, with the increase of the area of “Pavement” being the greatest. From 1998 to 2004, the proportion of impervious surface (building plus pavement) increased approximately 51%, while “Vegetation” and “Bare soil” decreased 24% and 27%, respectively.

Table 21. Summary of land cover and its changes in the Alta de Lisboa from 1998 to 2004

Land cover	**1998**		**2004**		**Relative change**	
	Area (m^2)	**Proportion (%)**	**Area (m^2)**	**Proportion (%)**	**Area (m^2)**	**Proportion (%)**
Bare soil	66194	41	21033	14	-45161	-27
Building	3541	2	20128	14	16587	12
Pavement	15789	10	71820	49	56031	39
Vegetation	74476	47	33151	23	-41325	-24

Table 22 shows the matrix that was derived from the Level 1 change detection results obtained from the feature-based method. The matrix details the land cover conversions from one land cover type to another between 1998 and 2004. In the matrix, the value in each of the cells indicates the area of land (m^2) that was converted from one land cover type to another. Table 23 indicates the percentage of change of 1998 classes in 2004.

Table 22. Land cover changes from 1998 to 2004 (m^2), derived from the feature-based post-classification method

To / **From**	**Bare soil (m^2)**	**Building (m^2)**	**Pavement (m^2)**	**Vegetation (m^2)**	**Total Row**
Bare soil	2042	10206	33532	11432	57212
Building	0	2468	1053	16	3536
Pavement	269	2010	10912	1272	14463
Vegetation	18721	5445	26324	20432	70922
Total column	21033	20128	71820	33151	146139

Table 23. Land cover changes from 1998 to 2004 (%), derived from the feature-based post-classification method

From \ To	Bare soil (%)	Building (%)	Pavement (%)	Vegetation (%)	Total Row
Bare soil	4	18	59	20	100
Building	0	70	30	0	100
Pavement	2	14	75	9	100
Vegetation	26	8	37	29	100

Note that the total area for each class of the 1998 map is different in Table 21 and Table 22, because the auxiliary classes "Building's façades" and "Shadows" were not considered in this analysis.

In the main diagonal are the unchanged areas, while outside are the changed ones. The matrix shows that major land cover conversions occurred from "Bare soil" and "Vegetation", in 1998, to "Pavement" in 2004 (33532 m^2 and 26324 m^2, or 59% and 37%), respectively. The new buildings in 2004 were constructed mainly in areas that were bare soil and vegetation in 1998.

It can also be concluded that only 22% of the area remained unchanged (sum of the grey cells of the table divided by the area of change analysis) in the period under analysis. The orange cells are false changed areas introduced by the different orthorectification processes that originated the two orthophotos under analyses. In fact, no element of the class was demolished in the study area, meaning that 30% of the class being indicated as change is wrong.

6.5.4 Accuracy Assessment of Buildings' Change Detection

The classifications and change detection results were visually compared, and a quantitative evaluation was performed. The process was conducted only for the "Building" classes, i.e., the transitions from and to "Building", assessing "Change" and "No Change" situations between 1998 and 2004. In the "No Change" class are all the features that were classified as "Building" in both 1998 and 2004. All other classes, from and to "Building", represent the "Change" class.

The validation of large-scale urban elements with the purpose of integrating a GIS database includes assessing: (1) the feature's thematic quality, (2) the level of completeness (lack of omission errors) and correctness (lack of commission errors), and 3) the geometric quality of the extracted features.

In this context, a set of indices that can help assess not only the thematic and quality of the detection, but also the geometric quality of objects extracted from VHR images were tested. To assess the thematic quality, the area of overlap between classified and reference data is used. A similar procedure was proposed by Shan and Lee (2005), where building and building blocks extracted from IKONOS imagery were evaluated using the proportion of the area of a building that is missed (underlap) or correct (overlap), and the percentage of the area of a detected building not corresponding to a reference building (extralap).

The completeness and correctness analysis are made using the centroids of the classified polygons and their intersection with the reference polygons. The geometry analysis is done by verifying the compliance of the extracted building and building blocks with the planimetric tolerance allowed for the position of a point in a map, according to the national mapping specifications (Table 12). The tolerances for the elevation were not taken into consideration in this study.

In this work, no sampling occurred, and all features from the built-up classes were assessed.

Reference map

For the study area there is no official map representing the 2004 situation. Furthermore, topographic maps represent the building footprint, whereas satellite or aerial imagery captures its roof. Due to these limitations, an independent interpreter created a reference map of building and building blocks by visual analysis and manual digitizing over the orthophoto from 2004. All the discernible features belonging to the class of interest were digitized, without limits of size or shape. No scale-dependent generalization was applied to this reference dataset. In this process other data sources were used to support and validate the visual analysis, such as aerial oblique photographs available at www.bing.com/maps (Figure 43).

The reference map identifies 42 building and building blocks in 2004, among which 13 were built between 1998 and 2004, and 29 already existed in 1998.

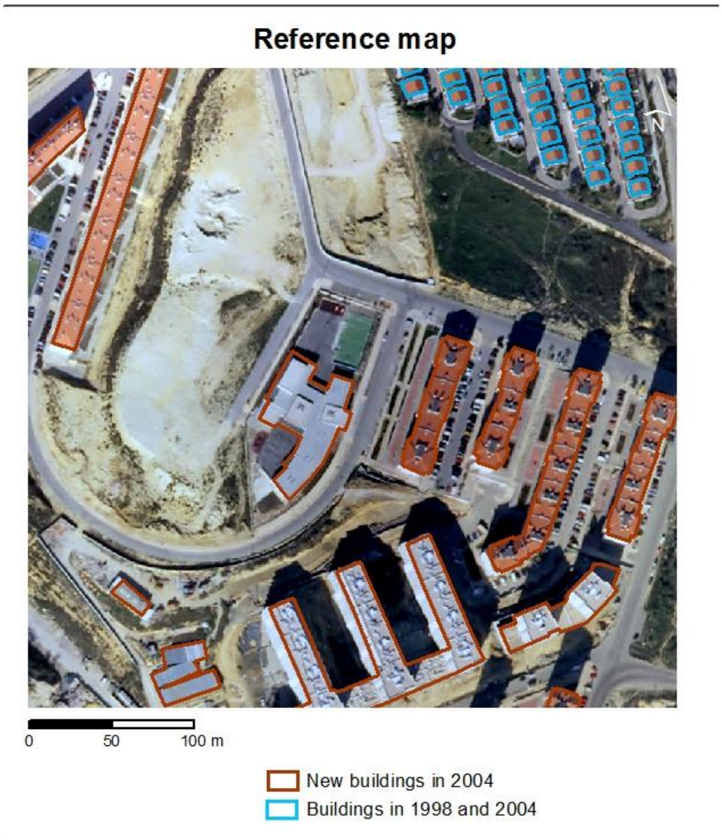


Figure 43. Reference map with the “Change” and “No Change” building and building blocks in Alta de Lisboa, obtained by visual analysis of the 1998 and 2004 orthophotos

Cartographic generalization

The reference map was obtained by photo-interpretation. Consequently, the digitized elements are cartographically generalized. To allow a proper comparison of the reference elements with the extracted ones, the “Change” and “No Change” classes were subject to a generalization process before map comparison. This post-processing was done in two stages: geometric simplification and elimination of small areas.

The features were subject to cartographic simplification using the ‘square up features’ tool, available in Feature Analyst. This tool allows straightening up the edges of polygons by squaring up the corners. This is helpful when extracting buildings or other essentially rectangular objects or that have only right angles. Four parameters are available: smoothing and squaring tolerances, cell size and fine tune rotation. The purpose of the smoothing tolerance is to apply the Bezier smoothing algorithm prior to squaring. The tolerance value is the distance in meters from shape edges where vertices are selected. The second parameter - the squaring tolerance - is the number of pixels in each line that will be moved in order to square up with the rest of the line segments. The cell size indicates the width of the image's pixel. The fine tune rotation specifies the orientation angle of the polygons.

The selected settings for the square up tool were 1 m for the smoothing tolerance, 6 pixels for the squaring tolerance, 0.5 m for cell size and no fine tune rotation. After geometric simplification, only extracted features with areas greater than 50 m^2 were considered for evaluation. This threshold represents the expected minimum building area, and reduces false alarms due to different relief orientation. Furthermore, all the building blocks in the study area have larger areas (Figure 44).

Figure 44. Building map derived from the post-classification change detection, after generalization

The classification map identified 48 building and building blocks in 2004, among which 19 are new elements, and 29 are unchanged building blocks.

Thematic accuracy of the Change class

The thematic accuracy was based on the overlay of the change classification and the reference map. The results were used to fill the error matrix and to calculate quality indices such as the overall accuracy, commission and omission errors. The two classes, “Change” and “No-Change”, were evaluated independently.

The “Change” class included all land cover classes in 1998 that changed to “Building” in 2004 (Figure 45). The error matrix was populated by overlaying the classified map with the Change reference map (Table 24). The Overall Accuracy index indicates 82% agreement between the map and the reference areas (Table 25). The Commission Error is very small, 5%, meaning that few areas were overestimated. The features that contribute to this error are located on the top right corner of the study area and correspond to “No-Change” building features that are misclassified due to the different building orientation between the two orthophotos. The Omission Error of 15% indicates that few areas were underestimated. This situation is visible along the borders of the new building blocks.

Table 24. Error matrix for the “Change” class

Ref. / Map	Change (m^2)	No-Change (m^2)	Total row
Change	1633	811	17144
No-Change	2816	0	2816
Total column	19148	811	19960

Table 25. Thematic accuracy of the “Change” class

Indices	Thematic (%)
Overall Accuracy	82
Commission Error	5
Omission Error	15

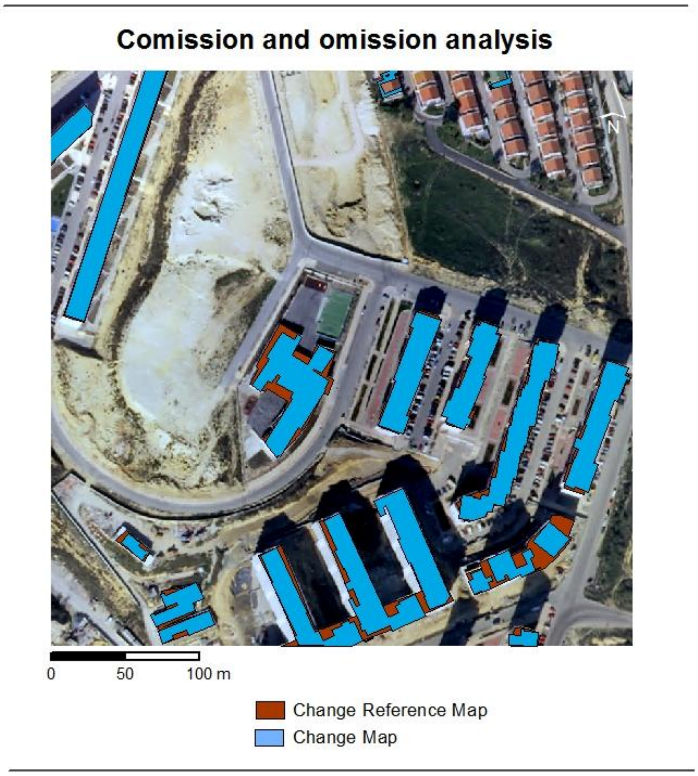


Figure 45. Overlay of the class mapped as Change with the reference

Thematic accuracy of the No-Change class

The “No-Change” class comprises the features that were classified as “Building” in 1998 and did not change to other land cover class, i.e., were also classified as “Building” in 2004 (Table 26). For this class, the Overall Accuracy indicated 72% of agreement between the classified map and the reference (Table 27). A Commission Error of 4% indicated that very few areas were overestimated by the classifier. The Omission Error was high (25%) but it was mainly due to different relief orientation, in the two data sets (Figure 46). This result was already expected as pointed out in Table 23, where 30% of the class was classified as “Pavement” in 2004. The values differ slightly (25-30%), due to the generalization process applied to the class “Building”.

Table 26. Error matrix for the “No-Change” class

Map / **Ref.**	**No-Change (m^2)**	**Change (m^2)**	**Total row**
No-Change	2156	82	2238
Change	748	0	748
Total column	2904	82	2986

Table 27. Results of thematic accuracies of the "No Change" class

Indices	Thematic (%)
Overall Accuracy	72
Commission Error	4
Omission Error	25

Figure 46. Mapped and reference features for "No-Change" areas

Completeness and Correctness accuracy

Completeness, also referred to as Producer's Accuracy, is the percentage of the total area of building and building blocks in the reference that were detected by the algorithm. Correctness, also referred to as User's Accuracy, indicates how well the detected building and building blocks match the reference (i.e., the real buildings). This metric is closely linked to the false alarm rate. The calculation of both metrics is based on the counting of True Positives (TP), False Negatives (FN) and False Positives (FP). TP is the number of building and building blocks present in both reference and classification maps. FN is the number of building and building blocks in the reference that were not detected in the classification, while FP is the number of building and building blocks that are detected by the algorithm, but that not exist in the reference map. A good classification should have both a high completeness and correctness.

The formulas for the calculation are presented in equations 3 and 4 (Rutzinger et al., 2009):

$$\text{Completeness} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad [3]$$

$$\text{Correctness} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad [4]$$

When evaluating the performance of an object-based map, one way of assessing the TP, FN and FP is using a reciprocal approach involving the features' centroids. However, TP for completeness analysis is not calculated as TP for correctness analysis. The first step is to calculate the central point for each building and building blocks in the data set. Then, following the methodology presented by Rutzinger et al. (2009), for each building and building blocks in the reference, the number of central points of detected buildings inside the building is counted (Figure 47). If this count is positive, the reference building is considered to be a TP for completeness, otherwise it is a FN. In a similar way, for each detected building and building block, the number of central points of reference buildings inside the building is counted (Figure 48). The detected building is considered to be a TP for correctness if this count is positive and, a FP otherwise.

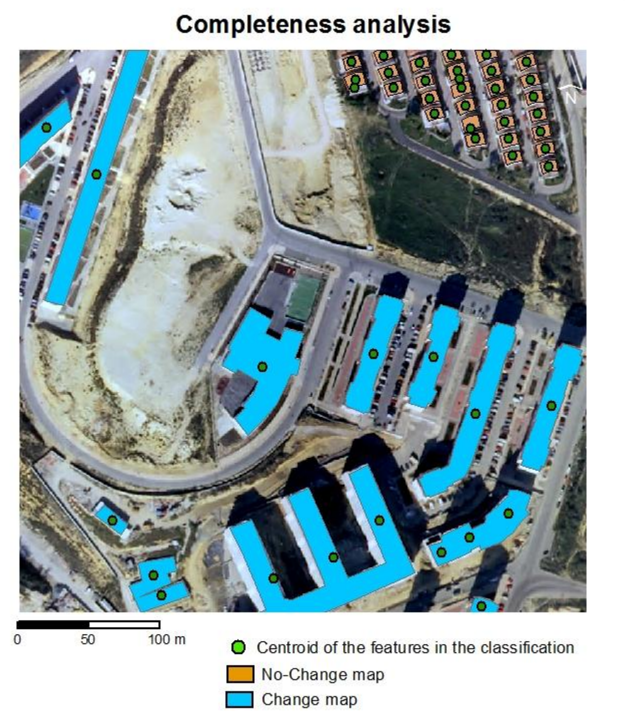


Figure 47. Completeness evaluation by overlaying classified feature's centroid on the reference map

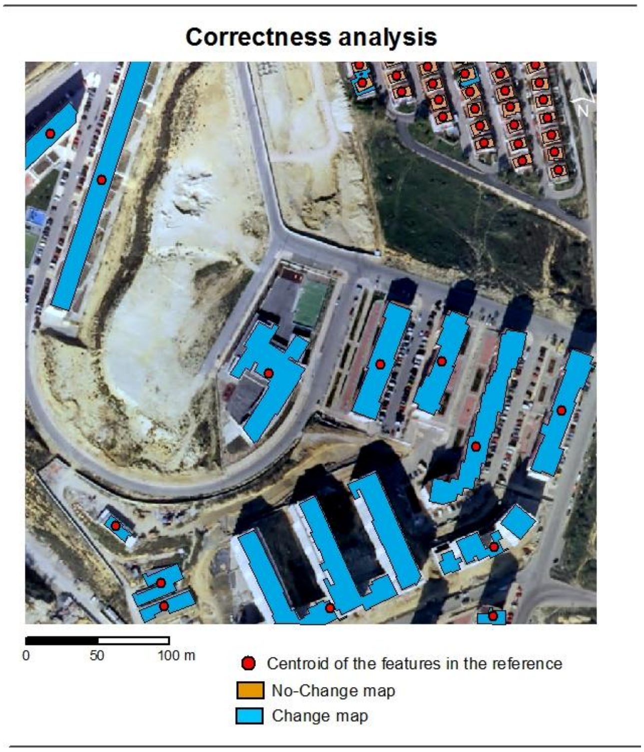


Figure 48. Correctness evaluation by overlaying reference feature's centroid on the classification map

The analysis was done for the whole map, and not for each class separately like the thematic accuracy procedure.

The result of the completeness analysis was 100%, meaning that all existent building and building blocks were represented in the classification map, and no omissions occurred. The result of correctness analysis was 95%, due to the fact that the classification detected two false changes, in the northwest part of the image. These are due to different building orientation between image dates.

Geometric accuracy

The evaluation of the geometric quality of the building and building blocks in the final map was made following the methodology described by Freire et al. (2010). While the thematic accuracies, completeness and correctness were evaluated for the entire building's class, the geometric quality is performed only for those class features that represent the same object in the reference and classification sets (1:1 relation).

Two types of analyses are used to evaluate the compliance with technical specifications: the area constraint and the sample based planimetric deviation. Imposing the area constraint on the extraction and reference data sets resulted in no change in the number of features. In fact, only features larger than 50 m^2 were considered as true changes in buildings, during the generalization step.

Planimetric tolerance is created for point-based testing. For the present application, it was adapted for verifying the compliance of polygons. Each reference feature was buffered using tolerances distances from the different mapping scales commonly applied by municipalities, and calculating the percentage of the extracted building outline that falls inside the tolerance, i.e. is compliant (Figure 49). The values for planimetric tolerance are presented in Table 12

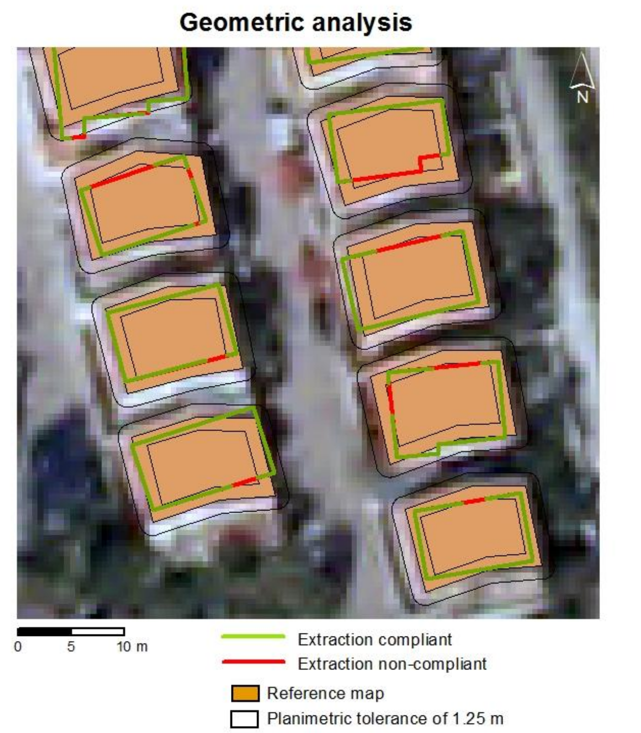


Figure 49. Detail of planimetric tolerance compliance test for scale 1:5 000

Since compliance with a RMSE standard is difficult to verify exhaustively in this way, verification of the 90% criteria was adopted instead, with the full building outline being analyzed. If 90% of more of the outline meets the tolerance, than the building's extraction agrees with the respective scale-specification.

The selection of polygons with 1:1 relation resulted in 40 pairs of polygons being compared. Results were not satisfactory for scales 1:1 000 and 1:5 000 (Table 28).

Table 28. Compliance values (%) for features for the 90% planimetric tolerance, by scale

	Scales		
Compliance	**1:1 000**	**1:5 000**	**1:10 000**
Min	3.2	33.4	56.0
Max	53.7	100	100
Mean	21.6	80.9	97.2
Std.	9.6	13.9	7.7
No. of features	0	13	36
% of features	0	33	90

For the largest scale, no features attained the 90% compliance value, while it was attained by only 33% of buildings at scale 1:5 000, with a mean value of compliance of 81%. At scale 1:10 000, 90% of features are compliant, with a mean compliance of 97%. These results are in line with those obtained by Gianinetto (2008) and Freire et al. (2010). However, one must keep in mind that this assessment is based on specifications designed for products where buildings are extracted manually in a 3D environment, where the commitment with those accuracy values is possible.

6.6 ALARM SYSTEM FOR LAND USE LAND COVER CHANGE IN URBAN AREAS

A multi-temporal strategy for updating a map using already existing cartography, a satellite image, and an altimetric data set, was applied in a study area located in the oriental part of Lisbon. The aim of this analysis is to highlight those areas where changes have most likely occurred. This new product, in a first step, can be analyzed by municipal technicians that: (1) will decide, based on analysis of the image and related information, if the marked spot is in fact a change area (a new urbanization or a built-up object that was demolished), and if so, (2) digitize the new buildings into the old cartography, or eliminate it, thus producing an updated map, if the *alarm layer* is accurate enough, or send a topographer to collect it directly. If the spot is considered to be a false detection, than the technician will (3) eliminate it. All these actions can be done using a GIS interface where the most recent building map is overlaid on the VHR imagery, and where attributes (e.g., from the Constraints Master Plan) can also be seen.

Such methodology can be used by the municipality to keep its cartographic database of urban areas up-to-date between two official map products, with higher thematic and positional accuracy.

The goal of this test is to produce updated information for the following classes present in the 1998 Municipal Cartography: “Buildings”, “Annexes” and “Shacks”.

6.6.1 STUDY AREA AND DATA SET

A cartographic update was experimented in the study area of “Madre de Deus”, located in the oriental part of the city of Lisbon. The selected area occupies 64 ha (800 m X 800 m) (Figure 50), and is characterized by a diverse land cover that includes herbaceous vegetation, lawns, trees and agricultural plots, bare soil, single and multi-family housing, a school, industrial properties, and roads and rail networks.

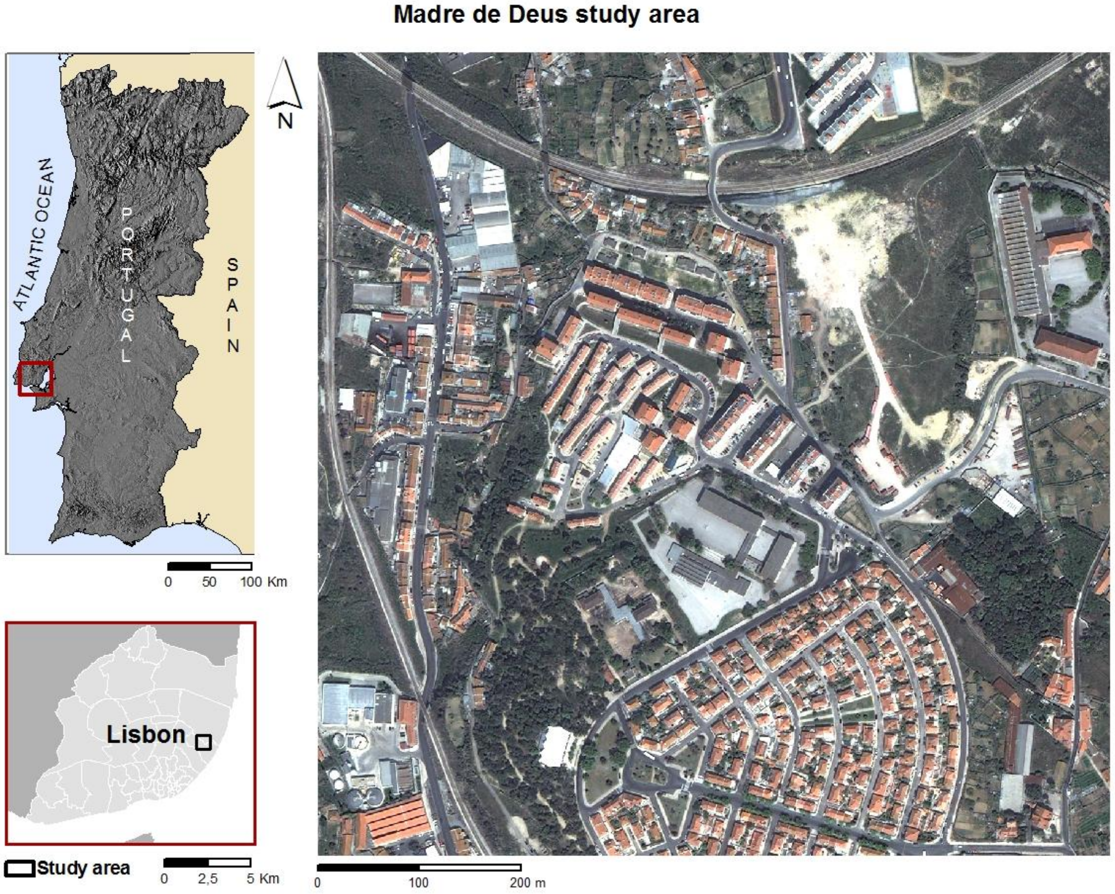


Figure 50. Location of the study area

The database explored in this case study included planimetric, spectral, and altimetric data:

- The map to be updated is the Lisbon's Municipal Cartography (Carto98);
- The altimetric data is composed by the normalized Digital Surface Model (nDSM) of the study area;
- The spectral data is the QuickBird image acquired in April 14, 2005.

6.6.2 Land Cover Classification for 2005/06

The first step for updating the Carto98 was to classify the QuickBird image from 2005, using the 2006 nDSM surface for better discrimination of the objects of interest (Santos et al., 2010a). The goal was to produce a Land Cover Map (LCM) for 2005/06.

The class of interest for map updating is the built up class. Nevertheless, other land cover classes are also considered in the classification system, in order to allow a good extraction. Regarding the building's rooftops, three classes were considered. One for the red tile cover, the most common material in the study area. Another class for the brighter roof material like light tin. And a class for remaining materials, that include dark tin, dark tile and fibrocement. Regarding the paved areas, three classes were identified: railways, roads and other impermeable surfaces that include streets, sidewalks and other paved material. Although present in the study area, a class for bare soil was not considered in this classification schema, since it did not affect the extraction of the built-up classes.

The nomenclature is organized in three levels of detail. The 1st level includes the classes “Urban” and “Vegetation”. On the 2nd level, three classes are defined: “Building”, “Pavement”, and “Vegetation”. On the 3rd level, seven classes are identified: “Building with red tile roof”, “Building with bright roofs” and, “Building with other roof”, “Road”, “Railway” and “Other impermeable surfaces”, and “Vegetation” (Table 29).

Table 29. Land cover nomenclature for 2005/06

Land cover classes in 2005/06		
Level 1	**Level 2**	**Level 3**
Urban	Building	Building with red tile roof
		Building with bright roof
		Building with other roof
	Pavement	Railway
		Road
		Other impermeable surfaces
Vegetation	Vegetation	Vegetation

The feature extraction was performed in Feature Analyst 4.2 (by Visual Learning Systems) for ArcGIS (ESRI). The classification is based on a supervised approach. The first step is the manual digitizing of training areas for each class, followed by the definition of parameters like the number of bands to be classified, the type of input representation, and aggregation.

For the extraction, several data sets were used simultaneously as input: pansharp and multispectral QuickBird imagery, the NDVI grid, and the nDSM layer. The pansharp QuickBird image is of fundamental importance because it is the main reflectance layer and determines the scale and resolution (spatial detail) that features can be extracted.

The approach selected in this work used, in a first stage, the possibility of classifying the study area in two major classes - “Vegetation”, “Urban” – and in the subsequent stages the level 3 classes were extracted independently. The parameters that produced the best extraction results for each element type are presented in Table 30.

Table 30. Parameters used for training the classifier to extract features in the study area

Class	Training areas (polygons)	Method & Window (pixels)	Aggregation (pixels)	Mask
Vegetation-Urban	167	Manhattan 5	10	-
Build. with red tile roof	24	Manhattan 5	10	Vegetation
Build. with bright roof	2	Manhattan 5	10	Vegetation
Railway	7	Bull's Eye 2, 9	400	Vegetation
Road	37	Bull's Eye 2, 7	50	Vegetation, Railway
Other imp. surfaces	13	Bull's Eye 2, 31	50	Vegetation, Railway, Road
Build. with other roofs	25	Manhattan 5	100	All precedent

The feature extraction stage was difficult due to the complex morphology and to the spatial heterogeneity of the study area. Several iterations took place after the initial training in order to obtain the final classes. Such operations included removing clutter and adding missing data to allow the classifier to learn and produce a better extraction.

Figure 51 shows the result of the best extraction for the level 2 class “Building”. The classifier was unable to identify single buildings in situations where two or more buildings were adjacent. In this case the building block was extracted.

Afterwards, a post-processing step took place. Several parameters were tested in the level 2 ‘”Building” class (Santos et al., 2010b). The ones that resulted better were operators available at ArcGIS 9.3: Aggregate Polygons tool, considering an aggregation distance of 10 m and a minimum area of 25 m^2, followed by the Boundary Clean tool, with expanding and shrinking performed once.

Figure 51. Building extraction in the study area

6.6.3 QUALITY ASSESSMENT OF THE BUILDING EXTRACTION

Since the goal is to update the built-up classes in Carto98, the quality assessment of the land cover extracted from the imagery dataset was applied only to the LCM level 2 class "Building".

To evaluate the quality of spatial information automatically extracted from images, based on the concept of reference value, it is necessary to measure levels of compliance with information from an independent source. This reference data was a map obtained by visual interpretation of the same source data. All the discernible features belonging to the class of interest were digitized, without limits of size or shape. To assess the overall thematic quality of building extraction, the spatial overlap between classified and reference data is used (Figure 52). This area-based test essentially evaluates the accuracy of the classification in terms of its extent and spatial distribution (Table 31).

Figure 52. Overlay of the extracted buildings on the reference map

Table 31. Error matrix for the “Building” class in the LCM

Ref. / Map	Building (m^2)	No Building (m^2)	Total row
Building	82738	4971	87708
No Building	25798	0	25798
Total column	108536	4971	113506

The analysis indicated an Overall Accuracy of 73% (Table 32). A 6% Commission Error was obtained. The fact that the image has an off-Nadir angle of 12.2º, and the LiDAR data has an orthogonal acquisition, made the extraction for taller buildings less accurate than for single family houses. This situation also contributes to the Omission Error of 24%. The omissions occurred mainly in places where roofs were in the shadow, or were in different states of conservation, or where elevator shafts were present.

Table 32. Results of thematic accuracies of “Building” class in the LCM

Indices	Thematic (%)
Overall Accuracy	73
Omission Error	24
Commission Error	6

In order to operationalize a methodology based on VHR data, higher commission errors are preferred over omission ones, because it is easear to delete uncorrect features than search for correct ones.

Regarding geometric quality, the shape of the extracted buildings was not very pleasing. A study (Freire et al., 2010) on the assessment of geometric quality and integrity of the extracted buildings, revealed that strict topographic standards of planimetric deviation were only met at scale 1:10 000, for a large percentage of extracted features.

6.6.4 Map Updating

Map updating begins by selecting the classes of interest from the Carto98 – “Buildings”, “Annexes” and “Shacks” (BAS) – and then evaluate their status based on two datasets: the nDSM from 2006 and the Land Cover Map from 2005/06 (LCM). These two datasets represent information of different years, however, most of the thematic information comes from the LCM. Therefore, for updating purposes, we considered that the final map represents the land cover of the study area in 2005.

The nDSM is used to characterize the average height of every element above ground. From the LCM, only three classes are used: the level 1 classes “Urban” and “Vegetation”, and the level 2 class “Building”. This option is due to the fact that the remaining level 2 class “Pavement”, only achieved a moderate overall accuracy of 65% (Santos et al., 2010a), making it not reliable enough for map updating.

The update is based on a change\no-change approach. Since we are analyzing built up classes, only three classes are possible in 2005/06: “No-Change” (class from 1998 is the same as in 2005/06), “Change to Vegetation” (removed features) or “Change to New Building” (built-up features):

- If an object is labeled as “No-Change”, then its class and geometry are the same as in the original Carto98;

– If an object is labeled as “Change”, then two classes are possible, “Vegetation” or “New Building”. The 1998 built up objects identified as “Vegetation” in the LCM, maintain their geometry and receive a new classification. The objects identified as “New Building”, have their geometry based on the LCM.

The update is done through map algebra operations over the available datasets, and follows four hierarchic rules (Figure 53):

– Rule 1 – every object identified as “Buildings”, “Annexes” or “Shacks” in 1998, and having height above 3 m in 2006, is labeled as No-Change T1 (From BAS To BAS);
– Rule 2 – every object identified as “Buildings”, “Annexes” or “Shacks” in 1998, having height smaller or equal to 3 m in 2006, and classified as “Urban” in LCM, is labeled as No-Change T2 (From BAS To BAS);
– Rule 3 – every object identified as “Buildings”, “Annexes” or “Shacks” in 1998, but classified as “Vegetation” in LCM, is labeled as Change T1 (From BAS To Vegetation);
– Rule 4 – every object not identified as “Buildings”, “Annexes” or “Shacks” in 1998, but greater than 1 m in 2006, and classified as “Buildings” in LCM, is labeled as Change T2 (To New Building);

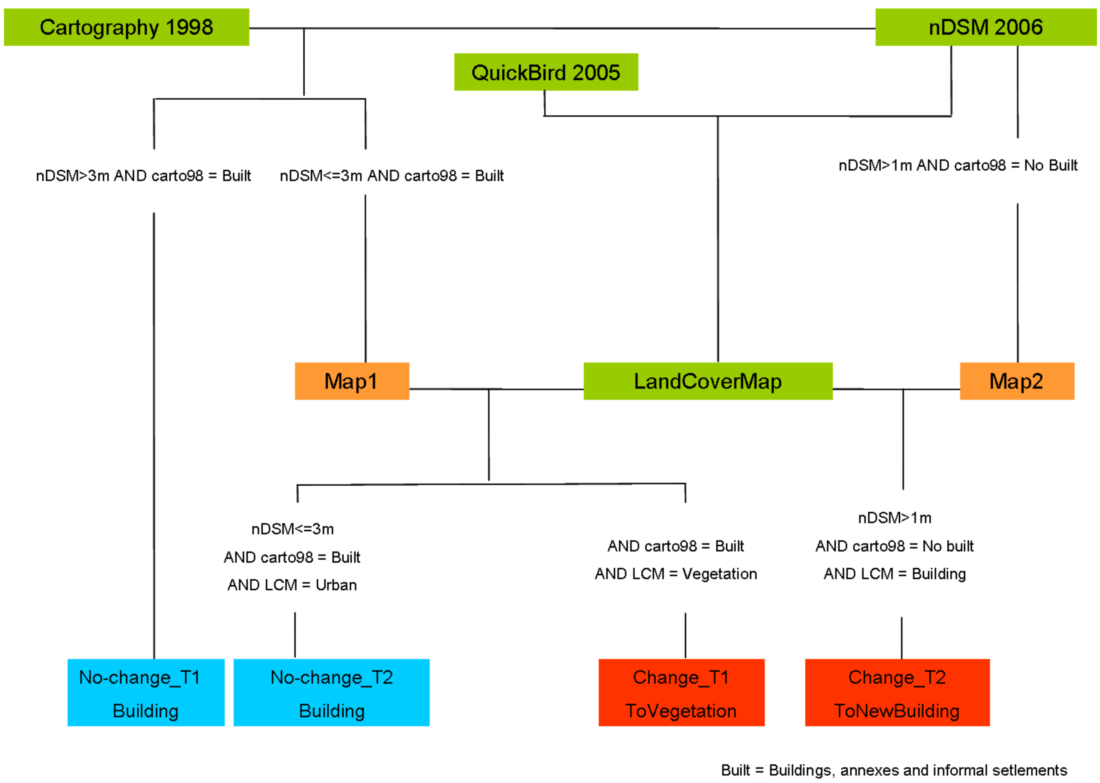


Figure 53. Updating schema

The final map of the study area, updated for 2005/06 (MapUp) according to the previous schema, has three classes: “No-Change”, “Change to Vegetation” and “Change to New Building” (Figure 54).

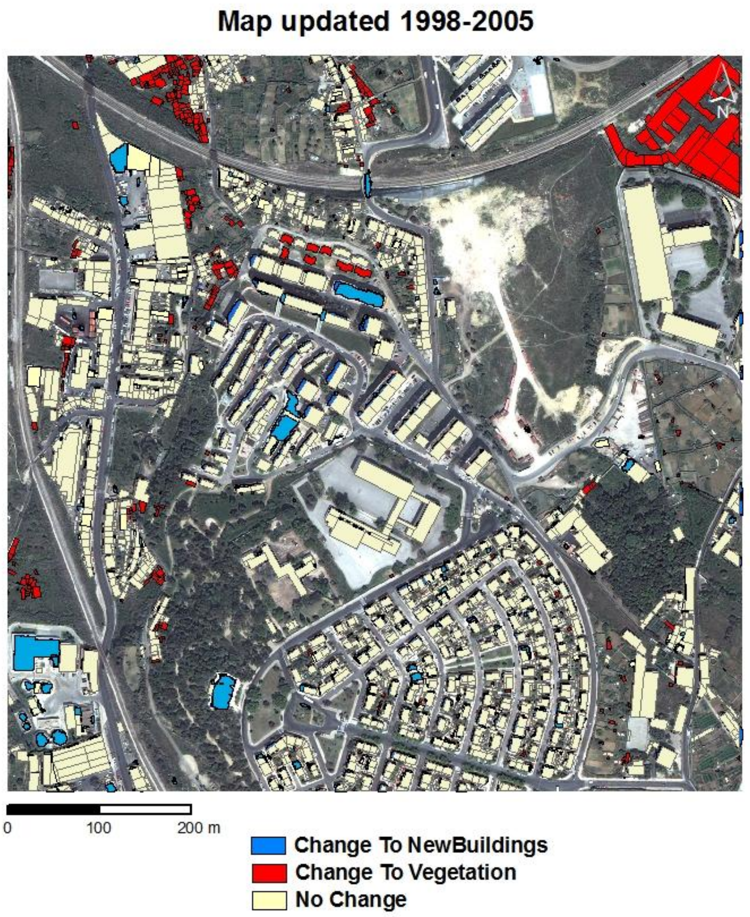


Figure 54. Map updated to 2005/06 (MapUp)

In the period under analysis – 1998 to 2005/06 – the main types of change identified in the study area were: shacks’ eradication and building demolitions (industrial properties), newly built industrial sites (e.g., the wastewater treatment plant, located in the bottom left corner of the map), as well as new residential housing (e.g., two multi-family buildings) (Table 33).

Table 33. Summary of the built up class and their changes in “Madre de Deus” from 1998 to 2005/06

Land cover	1998		2005/2006		Relative change	
	Area (m^2)	**Proportion (%)**	**Area (m^2)**	**Proportion (%)**	**Area (m^2)**	**Proportion (%)**
Buildings	98606	15	96477	15	-2129	0
Annexes	13869	2	12004	2	-1865	0
Shacks	10715	2	6289	1	-4426	-1

6.6.5 Quality of Detection of Building Change

After updating the map, its quality was evaluated based on visual interpretation. A census, instead of sampling approach, was conducted in order to fill the error matrix. Two analyses were performed: one for all the objects with area greater than 20 m^2, and another for all the objects with area greater than 10 m^2 and smaller or equal to 20 m^2. With this segmentation, we intend to evaluate the impact of smaller features on the map's quality. Objects having 10 m^2 or smaller were not evaluated since many of them are errors introduced by the misregistration between the QuickBird imagery and the LiDAR image and the Carto98.

Among all objects with an area larger than 20 m^2 that were visually inspected (1239 objects), 9 were excluded from the validation because the final class could not be confirmed with a sufficient level of confidence (Table 34). From this analysis, we can confirm that the class "Change To Vegetation" was well mapped. Only 3 features that were under trees were incorrectly classified as change. The "Change To New Building" was also very accurate, with no mistakes. The class "No-Change" was also well mapped, but had 15 misclassified features. From these, 13 objects were in fact demolished buildings that changed to road/pavement in 2005/2006. For further analysis the results of the validation were grouped into two classes – "Change" and "No-Change" - and an error matrix was populated (Table 35). Several indices were calculated to assess the quality of the objects larger than 20 m^2. From this analysis, we conclude that the updated map has an Overall Accuracy of 99% and a Kappa value of 95% (Table 36).

Table 34. Validation of the objects with areas larger than 20 m^2

Map \ Ref.	Change (objects)	No-Change (objects)
Change To Vegetation	151	3
Change To New Building	47	0
No-Change	15	1014

Table 35. Error matrix for the Change and No-Change objects with areas larger than 20 m^2

Ref. / Map	Change (objects)	No-Change (objects)	Total row
Change	198	3	201
No-Change	15	1014	1029
Total column	213	1017	1230

Table 36. Results of thematic accuracies of Change and No-Change objects with areas larger than 20 m^2

Indices	Thematic (%)
Overall Accuracy	99
Kappa	95
User's Accuracy for Change	99
User's Accuracy for No-Change	99
Producer's Accuracy for Change	93
Producer's Accuracy for No-Change	100

The same evaluation was made for those objects with area greater than 10 m^2 and smaller or equal to 20 m^2. From the total of 688 objects analyzed, 30 were rejected from the validation because the final land cover class could not be visually confirmed (Table 37). From the 116 objects classified as "Change To Vegetation", 14 were false changes located under trees. The accuracy of class "Change To New Building" was not very satisfactory, with 41 errors among the 69 validated objects. The "No-Change" class was well mapped, but several errors occurred, once more, in features that changed to pavement. From the error matrix, the thematic accuracy indices were calculated (Table 38). We conclude that the quality of the update for small objects is lower than those larger than 20 m^2, but still very high, with an Overall Accuracy of 89% and a Kappa value of 70% (Table 39).

Table 37. Validation of the objects with areas larger than 10 m^2 and smaller or equal to 20 m^2

Ref. / Map	Change (objects)	No-Change (objects)
Change To Vegetation	102	14
Change To New Building	28	41
No-Change	19	454

Table 38. Error matrix for the Change and No-Change objects with areas larger than 10 m^2 and smaller or equal to 20 m^2

Map \ Ref.	Change (objects)	No-Change (objects)	Total row
Change	130	55	185
No-Change	19	454	473
Total column	149	509	584

Table 39. Results of thematic accuracies of Change and No-Change objects with areas larger than 10 m^2 and smaller or equal to 20 m^2

Indices	Thematic (%)
Overall Accuracy	89
Kappa	70
User's Accuracy for Change	70
User's Accuracy for No-Change	96
Producer's Accuracy for Change	87
Producer's Accuracy for No-Change	89

6.6.6 User's Evaluation

To keep a municipal cartography up to date usually requires visual inspection of the database. The proposed methodology is based rather on an automatic verification and update of existing large-scale cartography, available in a GIS format, using image data as reference information. The advantage of the developed system is that it reduces the manual efforts of a human operator, saving time and, probably, costs, allowing concentrating attention only on those changed areas, and consequently, making it a more efficient process.

In order to evaluate the developed system, the final user – the municipality of Lisbon – was asked to test it and judged its applicability in a daily context. For this purpose, a GIS technician had to display the MapUp onto the QuickBird imagery of 2005. Two aspects were evaluated: the quality of the thematic information of the change and no-change areas and, the time spent using the alarm system to investigate the whole study area. The municipality's feedback was very encouraging. The test area was analyzed in only two hours, and was considered to be a good contribution for maintaining the database updated, since the change polygons could be easily marked for field inspection or be deleted when considered to be false changes.

6.7 SOLAR POTENTIAL ANALYSIS

The basic resource for all solar energy systems is the Sun. Knowledge of the quantity and quality of solar energy available at a specific location is of prime importance for the design of any solar energy system, since the greater the intensity of the light, the greater the available electricity (Stine and Geyer, 2001). Another important factor is the roof area available for solar panels. The building's height and the construction typologies influence the built-up surface area. Additionally, limitations such as roof orientation, inclination, location, shading, historical considerations, and other competing uses (such as elevators, chimneys, antennas, roof terraces or penthouses) determine the relation between built-up and roof-top available area (Izquierdo et al., 2008). Consequently, in a solar potential analysis at the building scale, three aspects should be examined:

- The amount of energy coming from the Sun – the physical potential;

  Although the solar radiation is relatively constant outside the Earth's atmosphere, local climate influences can cause wide variations in available insolation on the Earth's surface from site to site (Stine and Geyer, 2001). Parameters like turbidity and diffuse radiation must be set for the study area. Also the topographic impact is evaluated through the usage of a Digital Surface Model (DSM) of the study area. The variation in elevation, orientation (slope and aspect), and shadows cast by topographic features are then assessed and used to calculate the amount of insolation received at different locations;
- The location of the most suitable roofs to capture the solar energy – the geographic potential;

  In addition to estimating the amount of energy coming from the Sun, the design of a solar system must also take into account the position of the Sun and the buildings. The Sun's position must be known to forecast the amount of energy falling on tilted surfaces, and to determine the direction toward which a solar collector must be installed. Using a layer with the buildings footprints, and the roof's solar characteristics calculated in the previous step, the best locations for solar panels are elected;
- The characteristics of the solar panels – the technical potential

  The specifications of the equipment used to convert the solar resource into thermal or photovoltaic energy are variables that contribute for the technical potential of these systems. Features like module efficiency or panel's area must be considered in this step.

In this work, the goal is to evaluate the roof-top area suitable for installation of solar energy systems in the city of Lisbon. A brief technical analysis, considering the optimal location for solar photovoltaic systems is performed, but no economic or social parameters are addressed here. The general workflow is presented in Figure 55**.**

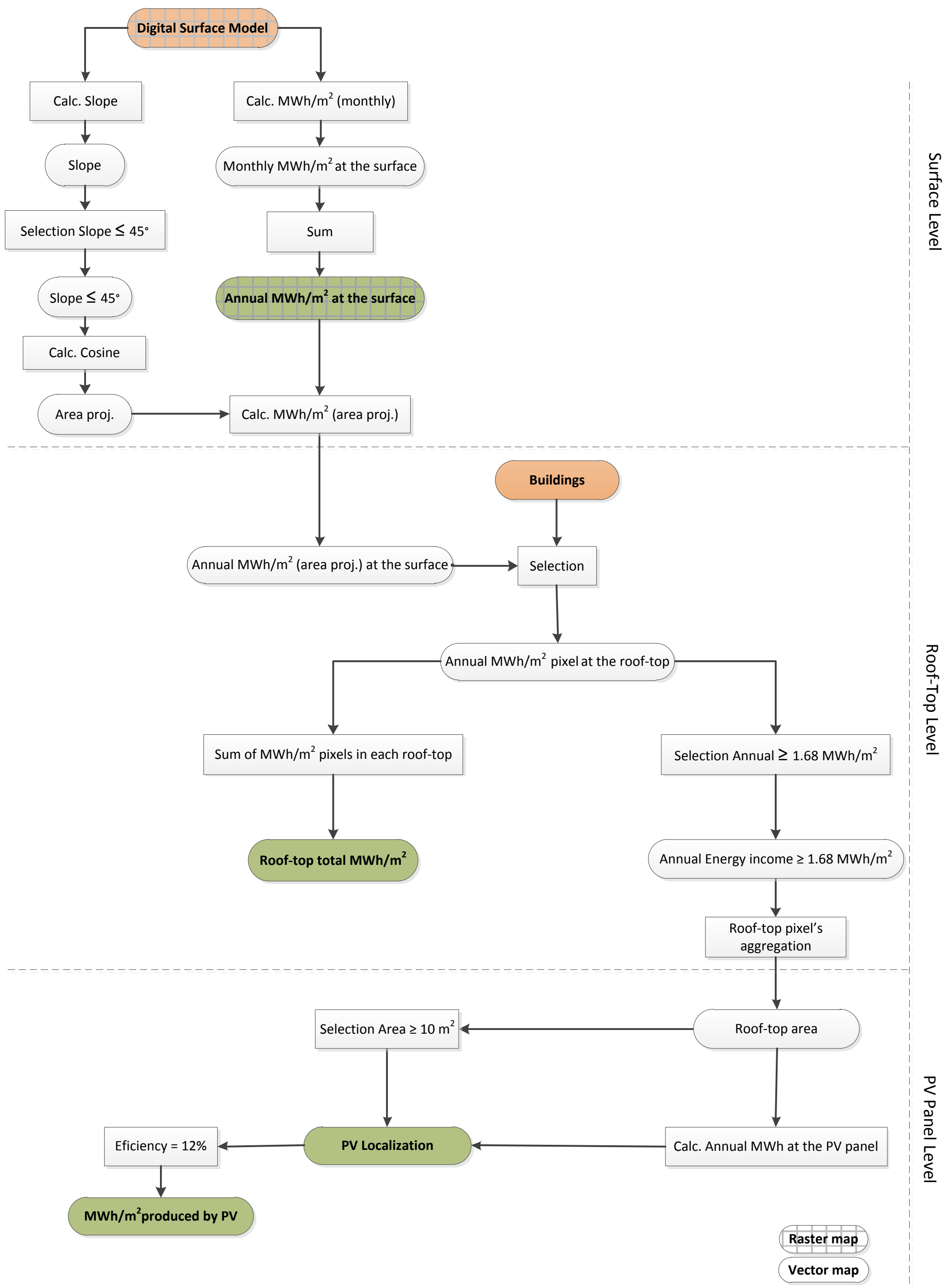


Figure 55. Proposed workflow for solar potential analysis. The orange boxes indicate input data and the green ones the output maps

6.7.1 STUDY AREA AND DATA SET

The experiment is applied in an area located in heart of the city of Lisbon – Avenidas Novas – that occupies 625 ha (2.5 X 2.5 km). The street network is dense and most of the area is built-up, including three major avenues (Av. República, Av. Fontes Pereira de Melo and Av. Liberdade), green areas (Parque Eduardo VII, Fundação Gulbenkian), multi-family housing, commercial areas and two university campus (Figure 56).

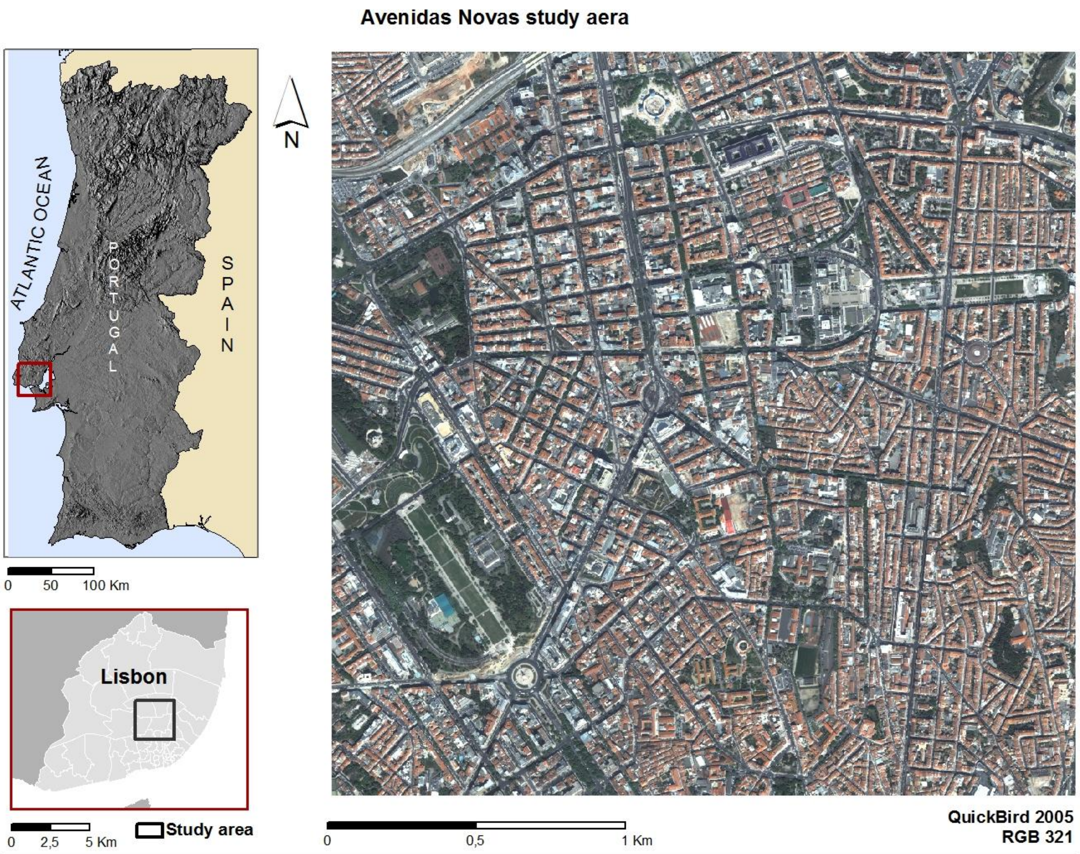


Figure 56. Study area for Solar Potential Analysis in Lisbon

The spatial database used in this case study included planimetric and altimetric data:

- The planimetric data that represents the buildings footprints is the Building's layer of the Municipal Cartography from 1998. This layer was extracted for the study area;
- To characterize the altimetry, the DSM and the nDSM from 2006 were selected.

6.7.2 SOLAR RADIATION AT THE SURFACE

The first methodological step for evaluating the solar potential of the study area, is obtaining the solar energy at the surface level. This is accomplished with the Area Solar Radiation tool, available in ArcGIS, that derives the total amount of incoming solar radiation (direct + diffuse) calculated for each location of the input raster surface. The diffuse proportion is the fraction of global normal radiation flux that is diffuse. The transmittivity is the ratio of solar radiation outside the atmosphere to that reaching the Earth's surface. The model accounts for site latitude and elevation, surface orientation, shadows cast by surrounding topography, daily and seasonal shifts in solar angle, and atmospheric attenuation (Fu and Rich, 1999). Therefore, by inputting the local DSM, the tool, after parameterization, produces a solar map that accounts for local topographic influences on solar radiation over the study area. This aspect is particularly important in urban areas, where shadowing effects are very common.

The Area Solar Radiation tool for ArcGIS allows characterizing the physical characteristics of the study area, regarding insolation, taking into account a user specified model (a DTM or, more desirable, a DSM). However, the annual values calculated by this tool differ from the ones produced by PVGIS. PVGIS only produces daily values for the city scale, based on surface model with 1 km resolution, derived from the USGS SRTM data. However, its estimations are reliable and were validated with values from local meteorological stations (JRC, 2010). Therefore, the reference values for radiation energy were the ones estimated by the PVGIS model at Lisbon’s latitude. To calibrate the solar parameters in ArcGIS in order to obtain energy values closer to the ones available at PVGIS, a model of a standard building with 0º (terrace), 34º (roof) and 90º (façades) was created and used in ArcGIS (Gomes, 2011). The diffusion and transmission where then assessed for each month (Table 40).

Table 40. The monthly parameters applied for the radiometric modeling (Gomes, 2011)

Month	**Diffusion**	**Transmittivity**
January	0.25	0.65
February	0.25	0.60
March	0.20	0.65
April	0.25	0.55
May	0.25	0.55
June	0.20	0.60
July	0.22	0.60
August	0.25	0.60
September	0.25	0.60
October	0.25	0.65
November	0.20	0.65
December	0.25	0.65

The Area Solar Radiation tool allows specifying the topographic and radiation parameters. The following were used for solar modeling in Lisbon:

– The input raster and time calculation parameters selected were:

In surface raster – the local DSM;

Out global radiation raster – month_1 (of 12);

Latitude – automatically calculated from the DSM;

Sky size – this is the resolution for the viewshed, sky map and Sun map grids. The default value for creating rasters of 200 X 200 cells was selected;

Time configuration – specifies the time period used for calculation. A time configuration of a whole year with monthly interval, creating an output for each month, was selected;

– The topographic parameters selected were:

Z factor - the number of ground x,y units in one surface z unit. In this study it was 1;

Slope and aspect input type – stands for how this information is derived for analysis. Calculation from the DSM was selected;

Calculation directions – indicates the number of azimuth directions used when calculating the viewshed. The default value of 32 was selected;

– The radiometric parameters selected were:

  Zenith and azimuth divisions – it is the number of divisions used to create sky sectors in the skymap. The default of eight divisions was selected;

  Type of diffuse radiation model – the uniform sky model considers that incoming diffuse radiation is the same from all sky directions. This option was selected.

– Diffuse and transmittivity proportions – as shown on Table 40.

The procedure was applied in a monthly basis, producing a solar map for each month. Then, all 12 maps were summed up and the annual solar radiation at the surface, in Wh/m^2, was calculated (SolarSurf). Figure 57 shows the DSM used as input for the Area Solar Radiation tool, and the solar radiation map produced (SolarSurf).

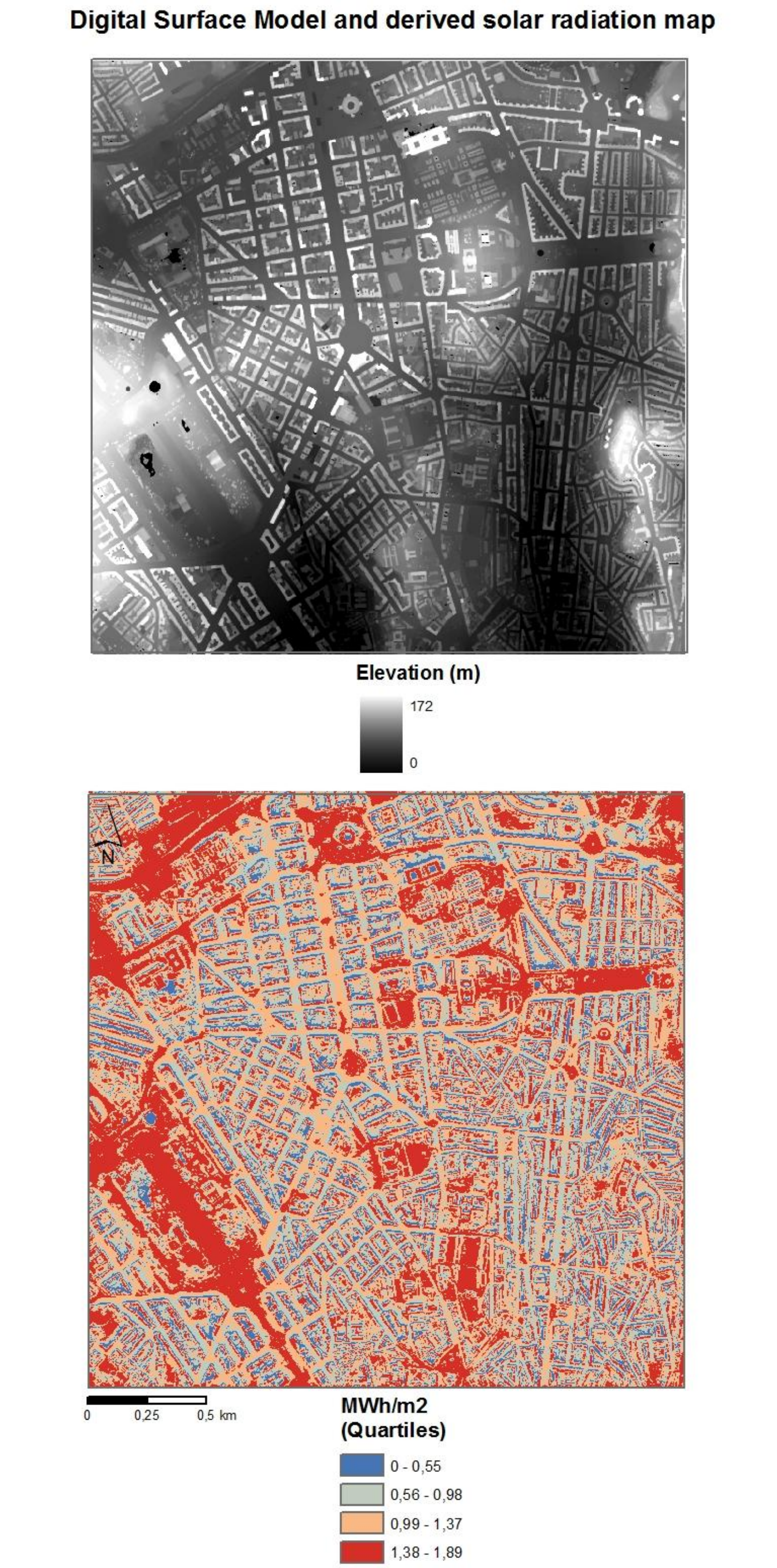


Figure 57. Digital Surface Model (DSM) and annual solar radiation map (SolarSurf) of the study area

6.7.2 SOLAR RADIATION ON THE ROOF-TOPS

The next step in analyzing the solar potential of the buildings of the study area is obtaining detailed information on the amount of radiation that reaches the roof-tops. So, after solar mapping at the surface, the solar radiation at the roof-top can be obtained using the building footprints.

Using the original planimetry from 1998 demonstrated to be inadequate to represent the built-up environment in 2006, the date of the DSM. The buildings retrieved from the 1998 cartography were then updated for 2006, using a methodology similar to the one described in the Alarm System application (section 6.6). The cartography was superimposed in the nDSM, and new buildings were digitized. The final map was topologically validated and only features greater than 10 m^2 were considered for further analysis. Approximately, 135 new elements were built between 1998 and 2006.

Due to DSM imprecision along the buildings' limits indicated on the Buildings layer, only pixels with values lower or equal to 45º in the slope map were selected for roof-top analysis. This value was empirically obtained with the intent of eliminating pixels with elevation values that corresponded to façades. Therefore, in the next step, when combining the SolarSurf with the Building layer, roof-top pixels were correctly identified. The number of buildings evaluated in the next analysis was then 12344. Furthermore, based on the DSM, the projected area of each pixel was calculated.

The SolarSurf, corrected for the pixel's projected area, was then combined with the Buildings' layer. This operation produced the map with annual solar radiation available at each pixel of the roof. Averaging the energy of all pixels of each roof, created the map with the mean annual solar radiation available at each roof-top (SolarRoof). Figure 58 shows the SolarRoof for the entire study area, and three close-ups, that detail the FCSH site (area 1), a high school (area 2) and two building blocks in downtown (area 3).

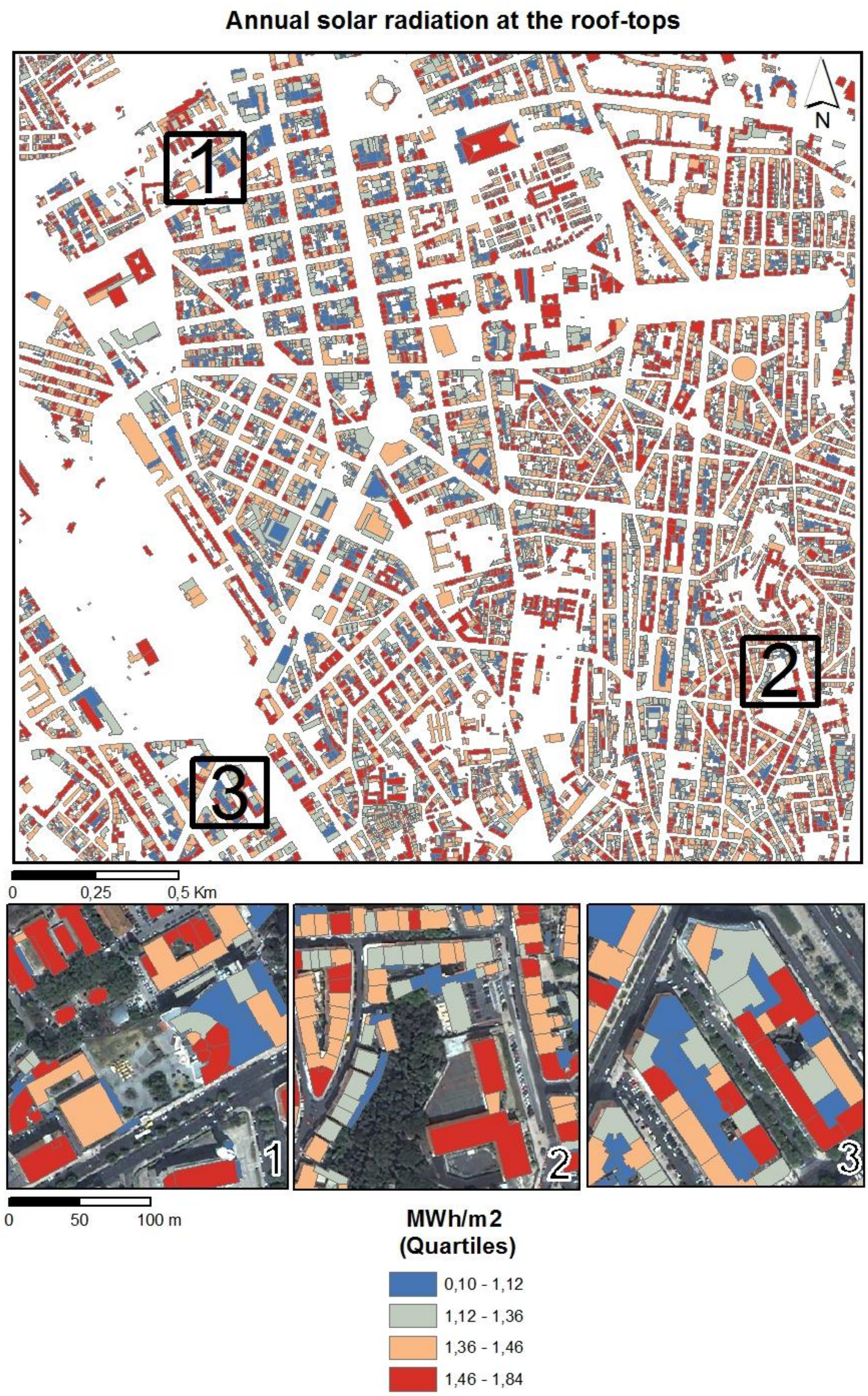


Figure 58. Mean annual solar radiation available at the roof-tops (SolarRoof)

6.7.3 BEST ROOF-TOP LOCATIONS FOR SOLAR PHOTOVOLTAIC SYSTEMS

After assessing the radiation at the roof-top, the selection of the best locations to install Photovoltaic (PV) panels was addressed. Two assumptions were considered: only pixels with annual radiation equal or higher than 1.68 MWh/m^2 were considered for PV installation (Gomes, 2011) and, due to the minimum requirements for solar system sizing, only the contiguous areas in each roof that were equal or higher than 10 m^2 were considered. Applying these constrains in the layer with the annual solar radiation available at each roof-top, the map with the location of each PV panel is calculated (Figure 59). As expected, the amount of buildings suitable for solar energy systems was lower than the original number investigated. In fact, from the initial 12344 buildings, only 6075 (49%) had good solar conditions and appropriate size to install PV panels, considering the solar and area limitations selected in this study.

Note that artifacts like roof overhangs, chimneys, dormers, antenna, were not considered by our methodology. To be integrated in this analysis, such identification requires more precise laser intensity values or additional spectral information.

Figure 59. Location of the photovoltaic panels in each roof-top

6.7.4 Energy Produced by Solar Photovoltaic Systems Located in the Most Suitable Roof-tops

At this stage, a brief technical analysis of photovoltaic panels is made. Only conversion efficiency is considered. This variable stands for the capability of solar cells for converting the energy of incoming light into electrical energy. Considering now that PV modules have a typical efficiency of 15% (Brito, 2009), and that of those 25% are lost in conversion (Šúri et al., 2007), the final efficiency of the PV system is 12%. Applying this value to the solar energy reaching the PV panels, an estimation of the annual photovoltaic energy produced at each roof-top was assessed (Figure 60). From this analysis, the building with the highest potential in the study area is the D. Luisa de Gusmão High School (area 2 in the figures), with an estimated production of 142.58 MWh, if the optimal roof area is all covered with PV panels (681 m^2).

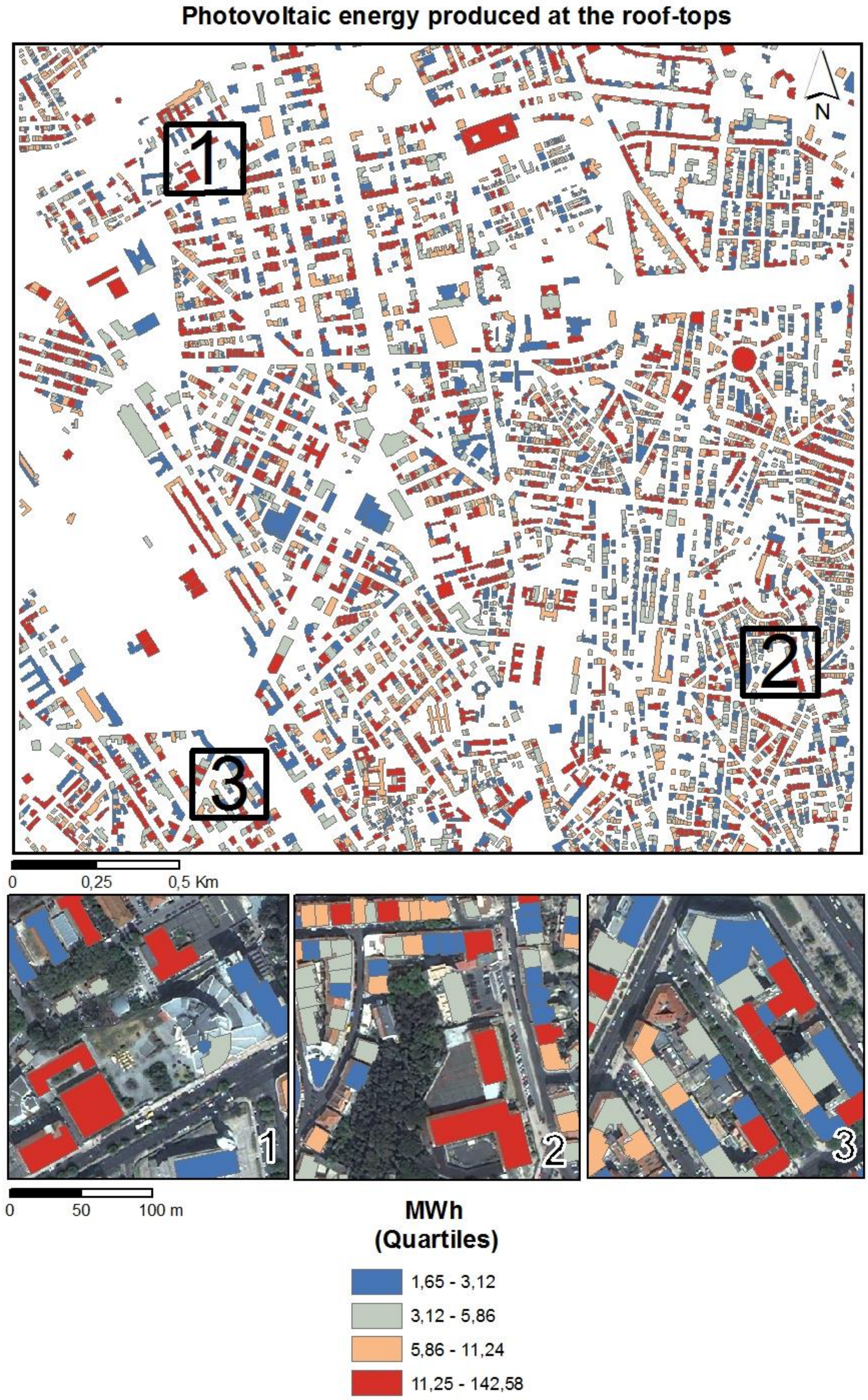


Figure 60. Energy produced annually by solar photovoltaic systems installed in roofs with best suitable

6.8 URBAN ENVIRONMENT QUALITY INDICATORS

The first step in extracting geographic information for building indicators is the production of LCMs. The present work details the development of an updated and detailed map of imperviousness for the city of Lisbon using satellite imagery. The Vegetation-Impervious-Soil (VIS) model, developed by Ridd (1995), is used as the basis for extracting land cover information at the city-scale. It is a conceptual representation that allows simplifying the analysis of urban surfaces by decomposing it in three basic land cover components: vegetation, impervious surface and soil.

After collecting data on land cover from remote sensing data, several applications can be demonstrated. Indicators on land sealing area, quantification of green area, or the available soil in the city, are ecological measures that can be used for monitoring and analyzing trends over the territory. Studies on impacts of urbanization, responses to natural and man-made disasters, vulnerability analysis or housing conditions, all require updated land cover information. In this case study, we propose two types of indicators: indicators strictly assessed from VHR imagery (Table 41), and indicators based on VHR imagery and census data for the city level (Table 42).

Table 41. Urban environmental indicators strictly based on very high-resolution imagery

Component	Indicator	Definition	Unit
Vegetation	Surface occupied by Green Areas	Green area/ City area*100	%
	Surface covered by Trees	Tree area/ City area*100	%
Soil	Soil available in the city	Soil area/ City area*100	%
Impervious	Impervious area available in the city	Impervious area/ City area*100	%
	Building area available in the city	Building area/ City area*100	%
	Impervious area that is occupied by Building	Building area / Impervious area*100	%
Vegetation Impervious	Green area vs. impervious area	Green area/ Impervious area	
Vegetation Impervious Soil	Pervious area vs. impervious area	(Green area + Soil area)/ Impervious area	

Table 42. Urban environmental indicators based on very high-resolution imagery and census data

Indicator	Definition	Unit
Green area per capita	Green area/Inhabitant	m^2/inhab
Impervious area per capita	Impervious area/Inhabitant	m^2/inhab
Area of buildings per capita	Building area/ Inhabitant	m^2/inhab
Liquid population density	Inhabitants/ Building area	inhab/ m^2
Soil per capita	Soil area/ Inhabitant	m^2/inhab
Pervious area per capita	(Green area + Soil area)/ Inhabitant	m^2/inhab

6.8.1 STUDY AREA AND DATA SET

The study area, where geographic information extraction is tested for building urban indicators, is the city of Lisbon (Figure 61). The municipality occupies an area of 84 Km^2, and is a typical European capital city, with a very diverse land use dynamics, going from historical neighborhoods (e.g., the downtown area of *Baixa*), where the street network is dense and the most of the area is built-up, to modern residential ones (e.g., the area of Alta), with on-going construction of roads and multi-family buildings. Between these two situations, there are more heterogeneous places with land uses that go from built-up, parks, agriculture and vacant land to industrial, utilities, and schools.

The spatial database used in this case study included the 2008 IKONOS pansharp image of the city and the computed NDVI, and the nDSM form 2006.

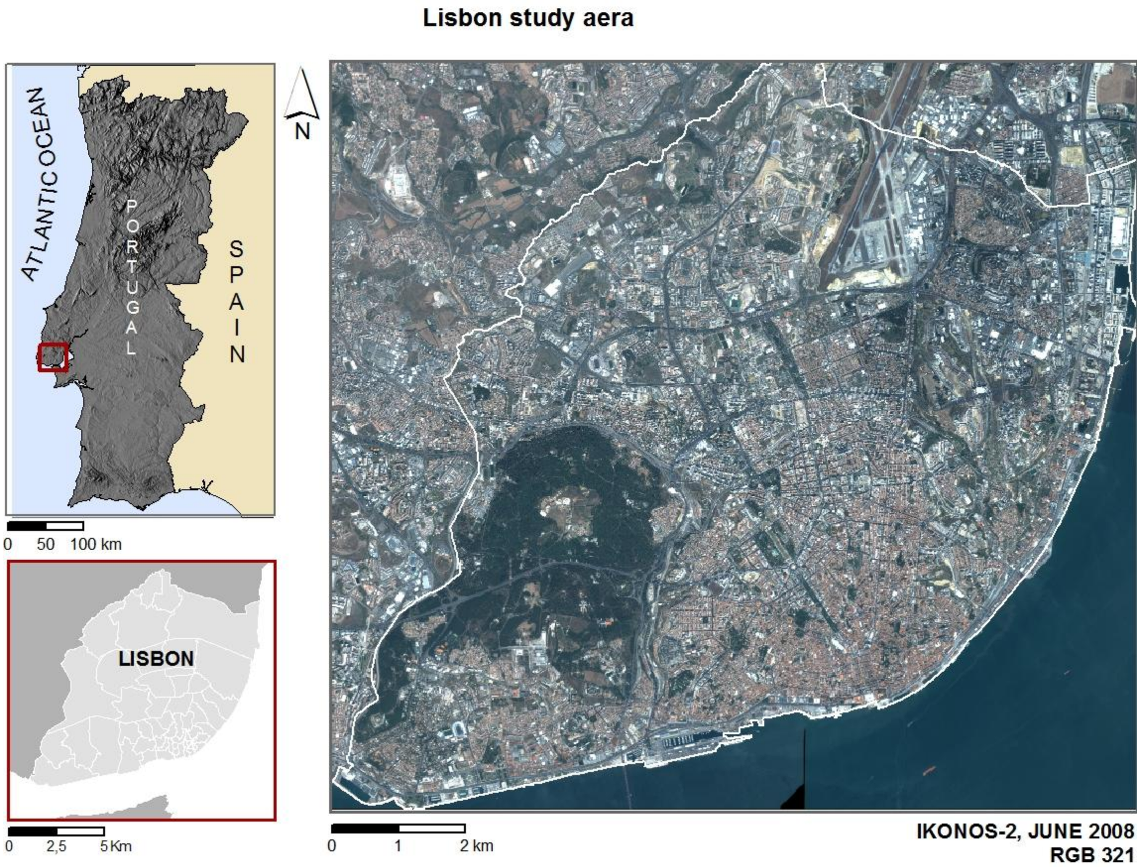


Figure 61. Study area for deriving Urban Indicators in Lisbon

6.8.2 Land Cover Extraction

The nomenclature is organized in two levels of detail, following the VIS model, but including also a shadow and water class, more adapted to the urban environment. The 1st level includes the classes "Vegetation", "Impervious Surfaces", "Soil", and "Shadows and Water". On the 2nd level, seven classes were defined: "Trees", "Low Vegetation", "Buildings", "Roads", "Other impervious surfaces", "Soil", and "Shadows and Water" (Table 43):

- Green areas are an important land use in urban areas which perform relevant environmental functions, such as improving urban climate, reducing atmospheric pollution, providing amenities, aesthetical benefits and a good environment for urban population. Green land cover includes trees, shrubland, herbaceous vegetation, parks, private gardens, and agricultural plots;
- Impervious surfaces can generally be defined as anthropogenic features, such as roads, buildings, sidewalks and parking lots, through which water cannot infiltrate into the soil. The artificial surface cover can be used to evaluate the quality of urban

streams, and to study effects of runoff. Impervious surface is increasingly recognized as a key indicator for assessing the sustainability of land use changes due to urban growth;

– Soil is vacant land and is usually comprised of soil with little vegetation, thin soil, sand or rocks;
– Shadows occur in remotely sensed imagery when objects totally or partially occlude the direct light from a source of illumination, which include cast shadows (shadows cast on the ground, or on other objects, by high-rise objects), and self shadows (the part of the object that is not illuminated) (Salvador et al., 2001). Great difficulty arises in classification and interpretation of shaded objects in an image due to the reduction or total loss of spectral information of those shaded objects (Dare, 2005). This issue is particularly significant in urban environments where tall buildings are often present. Water is included in the same class as shadow, since both are dark objects in the image that will not be used for producing urban indicators.

Table 43. Land Cover nomenclature

Level 1	**Level 2**
Vegetation	Trees
	Low vegetation
Impervious surface	Buildings
	Roads
	Other impervious surfaces
Soil	Soil
Shadow and Water	Shadow and Water

Extracting Shadow and Water

Dark objects, that include both water and shadows, were extracted with a histogram thresholding method. A synthetic brightness image was initially computed though the mean value of the NIR, red and green bands and then a pixel-based histogram of brightness was analyzed to determine an optimum threshold value for shadows and non-shadows (a threshold value of 170 was set). As mentioned by Zhou et al. (2009), this histogram is bimodal, with the lower part being occupied by the darker features (shadows and water). In our case study, the selected threshold included shadows and deep water bodies.

Extracting Vegetation

The vegetation extraction was conducted for the unclassified areas (i.e., no shadow or water elements). In order to separate vegetated from non-vegetated surfaces in the urban environment, the Normalized Difference Vegetation Index (NDVI) was used, based on the pansharp image. A threshold of 0.22 was determined depending on the intensity values to mask the vegetated regions. This layer stands for the level 1 class “Vegetation” and includes the city’s green surface.

In the 2nd level of the nomenclature, two classes were distinguished: “Trees” and “Low Vegetation”. The first class identifies trees and tall bushes, whereas the other identifies lawns and other herbaceous vegetation. The “Trees” were extracted with FA using 8 training areas, the pansharp and the NDVI image, Bull Eye’s 3 for the input representation, width 5, masking in the level 1 class “Vegetation”, and 5 pixels of aggregation. After training the classifier, the final map was obtained after one ‘add missing areas’ process. The low vegetation class was the remaining vegetation.

Extracting Soil

The next major class to be extracted was “Soil”, and was applied in the unclassified areas (i.e., no shadow, no water, and no vegetation). The dataset included the pansharp image and the nDSM. The classifiers’ learning was done in two independent extractions, considering two types of soil classes: bare land with some earth, and thin soil. Bare land was extracted with the Manhattan algorithm, width 3, and 100 pixels of aggregation, and the other class with the same algorithm, but considering 50 pixels for aggregation. The bare soil was subject to an iteration of removing clutter.

The final step was the generalization of the soil polygons using the aggregate polygons tool from ArcGIS. The parameters were merging polygons that distance 2 m, and considering areas grater or equal to 100 m^2.

Extracting Impervious Surface

The map of impervious areas includes a wide range of materials, some of which have very different spectral properties (e.g., pavement, concrete, roof tiles, etc.). The 1st level class “Impervious Surface” corresponds to the land surface after masking out the “Vegetation”, “Soil”, “Shadow”, and “Water” classes. In the 2nd level of the nomenclature, three classes were distinguished: “Buildings”, “Roads” and “Others”, based on the pansharp image and the nDSM.

"Buildings" were extracted in three stages, considering different roof materials. For the red tiles, the parameters used were Manhattan representation, width 7, and 75 pixels of aggregation. For the darker roof materials and for the brighter ones, Manhattan representation, width 7, and 100 pixels of aggregation were the selected parameters. All learning's were followed by remove clutter or add missing data iterations to reach the final "Buildings" class. The last step included generalize the building polygons using the same parameters as for the "Soil" class: merging polygons that distance 2 m, and considering areas grater or equal to 100 m^2.

The class "Roads" was extracted in three independent processes, using different parameters. For the larger roads, Bull's Eye 2, width 25, and 1100 pixels of aggregation were considered. For the narrow roads, Bull's Eye 2, width 19, and 500 pixels of aggregation were considered. The remaining asphalt pavement was extracted with Bull's Eye 2, width 25, and 500 pixels of aggregation. These three layers were then merged to produce the "Roads" class. The final layer was obtained by generalization, using 2 m as merging distance and 100 m^2 as minimum area.

The "Other impervious surfaces" (like sidewalks or railroads), were the remaining areas within the "Impervious surface" class, after masking out the "Buildings" and "Roads" classes.

Figure 62 shows the final Land Cover Map produced for 2008, for the city of Lisbon, using satellite and LiDAR data.

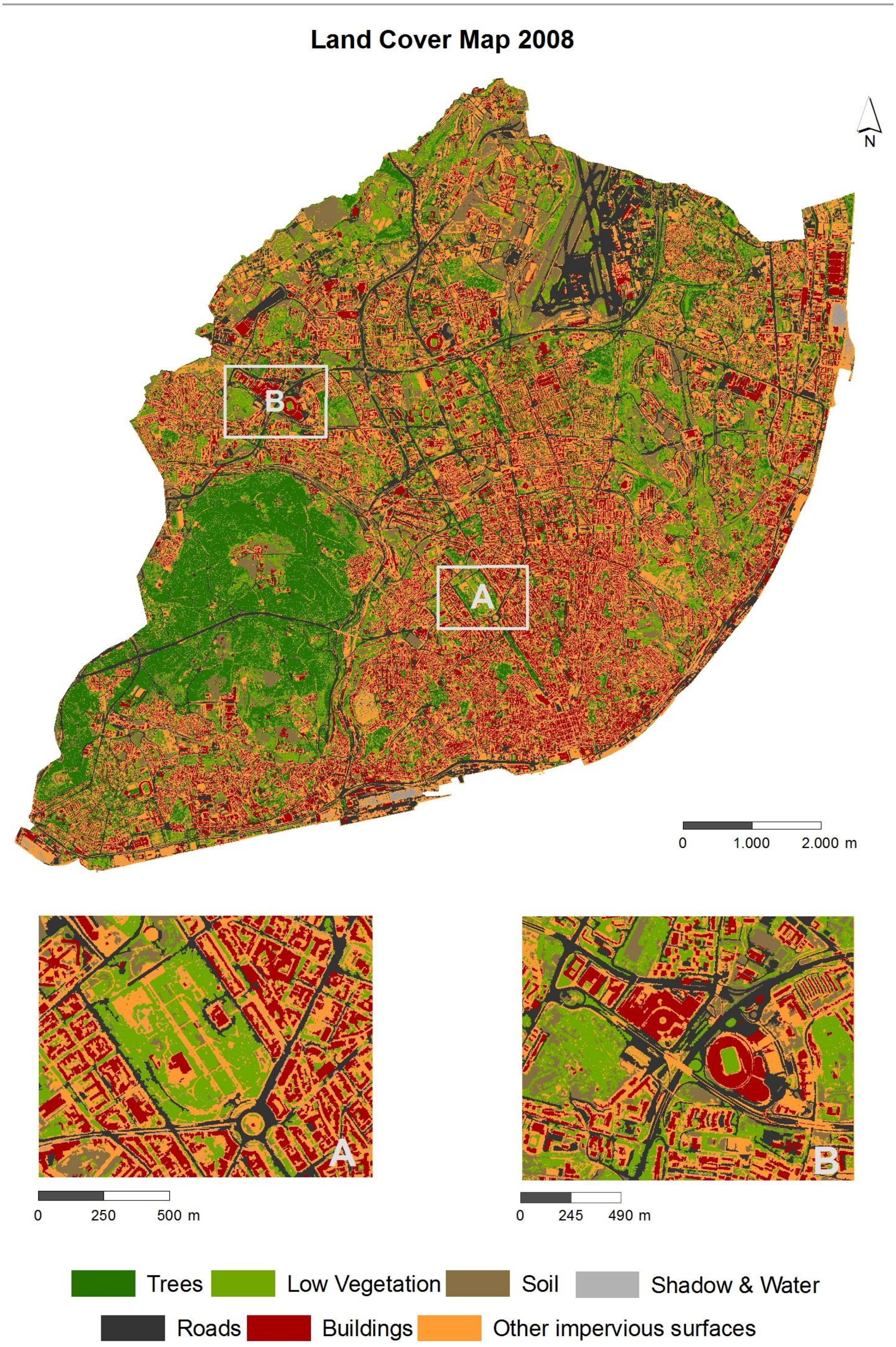


Figure 62. Land Cover Map of 2008 derived from IKONOS imagery for the city of Lisbon

6.8.3 ACCURACY ASSESSMENT OF LAND COVER MAP 2008

The thematic accuracy of the LCM2008 was evaluated based on a stratified random sampling. For each strata (i.e, each level 2 land cover class), 100 random points were analysed through visual analysis of the imagery and ancillary data. From the 700 samples, 2 were excluded from the evaluation because it was not possible to correctly identify the class. The samples were then used to build the error matrix and to derive thematic accuracy indexes (Table 44, Table 45). From this analysis, we conclude that the LCM2008 has an Overall Accuracy of 89% and a KHAT statistic of 87%, in the most detailed level. These values indicate great agreement between the reference data and the classified map.

Table 44. Error matrix for the LCM2008

Ref. / **Map**	**Trees**	**Low veg.**	**Buildings**	**Roads**	**Other imp. surfaces**	**Soil**	**Shadow and Water**	**Total row**
Trees	96	4	0	0	0	0	0	100
Low vegetation	23	72	0	1	2	2	1	101
Buildings	0	0	98	0	0	2	0	100
Roads	0	0	4	91	5		0	100
Other imp. surfaces	0	1	8	2	72	3	13	99
Soil	0	2	4	0	1	91	0	98
Shadow and Water	0	0	0	0	0	0	100	0
Total column	119	79	114	94	80	98	114	698

Table 45. Results of thematic accuracies of the LCM2008

Overall Accuracy = 89%, Kappa = 87%		
Level 2 Class	**Comission Error (%)**	**Omission Error (%)**
Trees	4	19
Low vegetation	29	9
Buildings	2	14
Roads	9	3
Other impervious surfaces	27	10
Soil	7	7
Shadow and Water	0	12

6.8.4 BUILDING URBAN INDICATORS

From LCM2008, two variables are extracted for building the proposed urban indicators: the area (Table 46) and the spatial distribution of each land cover class in the city (Figure 62). Using the area of each land cover, urban environmental indicators strictly based on VHR imagery can be assessed (Table 47). Using the area and demographic data allows assessing urban environmental indicators based on VHR imagery and census data, at the city-scale (Table 48).

Table 46. Areas of the level 1 and 2 land cover classes in the city of Lisbon

Level 1	Area (ha)	Level 2	Area (ha)
Vegetation	2428	Trees	1101
		Low vegetation	1327
Impervious surface	4907	Buildings	1213
		Roads	1352
		Other impervious surfaces	2342
Soil	839	Soil	839
Shadow and Water	299	Shadow and Water	299

Table 47. Urban indicators based on VHR data, in the city of Lisbon

Indicator based on VHR data	Value
Surface occupied by Green Areas	29%
Surface covered by Trees	13%
Soil available in the city	10%
Impervious area available in the city	58%
Building area available in the city	14%
Impervious area that is occupied by Building	24%
Green area vs. impervious area	0.5
Pervious area vs. impervious area	0.7

The value of Lisbon's population used to build the following indicators was obtained in the 2001 census (INE, 2001).

Table 48. Urban indicators based on VHR and demographic data, in the city of Lisbon

Indicator based on VHR and demographic data	Value
Green area per capita	43 m^2/inhab
Impervious area per capita	87 m^2/inhab
Area of buildings per capita	21 m^2/inhab
Liquid population density	0.05 inhab/ m^2
Soil per capita	15 m^2/inhab
Pervious area per capita	58 m^2/inhab

The LCM2008 provides a detailed and cost-effective digital map of the city of Lisbon. This case study demonstrates the utility of land cover mapping for building urban indicators for monitorizing planning actions. The mapping methodology presented, ensures that urban planners have updated data on land cover in a regular basis. This tool can be used for monitoring the incidence of land cover change within the city, decide on which areas of priority intervention, or assess natural resource sites for preservation and restoration.

6.8.5 Comparing Land Cover Map 2008 with Similar Maps

The Urban Atlas is a European product, produced by visual interpretation of satellite data, with the support of reference data. For urban areas, a minimum mapping unit of 0.25 ha is considered. This map is available for Lisbon, and was based in ALOS imagery (spatial resolution of 2.5 m), from 2007. The goal of the Urban Atlas is to provide land use information for compiling environmental indicators. Based on the fact that Urban Atlas and LCM2008 both share the same objective, and are obtained from EO data, a comparison of results is presented.

The area of each class in level 1 of LCM2008 was compared with the corresponding level 1 and the more disaggregate level of the Urban Atlas map (level 4), from 2007 (Appendix 2). The class “Shadows and Water” was excluded from this analysis. This option introduced differences in the total area of each maps (Table 49)

Table 49. Comparing areas from LCM2008 level 1 classes and Urban Atlas, in the city of Lisbon

LCM2008 class	Total Area (ha)	Urban Atlas class	Total Area (ha)	Difference Area (ha)
Vegetation	2428	14100; 14200; 2000; 3000	1980	448
Impervious surface	4907	11100; 11200; 11210; 11220; 11230; 11300; 12100; 12200; 12210; 12220; 12230; 12300; 12400	6117	1210
Soil	839	13100; 13300; 13400	313	526

The most obvious differences are found in “Impervious surface” and “Soil” class areas. The reason for these differences lies in the technical characteristics regarding the mapping process: the minimum mapping unit and the choice of a nomenclature almost exclusively based on land use, rather than a nomenclature that prioritizes land cover.

In the LCM2008, a minimum mapping unit of 100 m^2 was selected for “Impervious surface” and “Soil” classes, and 1 m^2 for “Vegetation”. In the Urban Atlas, the minimum mapping unit is 0.25 ha (2500 m^2) for urban classes, and 1 ha for non-urban classes. This situation compromises the representation of vegetation within city blocks in the Urban Atlas, whereas the same did not occur in LCM2008. This fact contributed to the higher area of the impervious surface (6177 ha) reported in Urban Atlas, when comparing with LCM2008 (4907 ha).

Urban Atlas uses a nomenclature based on the CLC, which gives priority to land use over land cover. LCM2008, on the other hand is more concerned with land cover. This fact, along with the minimum mapping unit, also contributes to different classes’ areas, when comparing the two maps. For example, the public park *Jardim da Estrela*, that occupies an area of approximately 6 ha, it is classified as “Impervious surface” in the Urban Atlas, while in LCM2008 it is mainly classified as “Vegetation”, “Impervious surface” and “Soil” (Figura 66). When using the most disaggregate nomenclature from both maps, it is also evident that the estimation of green surface, when using the Urban Atlas map is much different than the one mapped in LCM2008 (Figura 63). The same situation occurs in the *Gulbenkian Garden* that occupies approximately 9 ha.

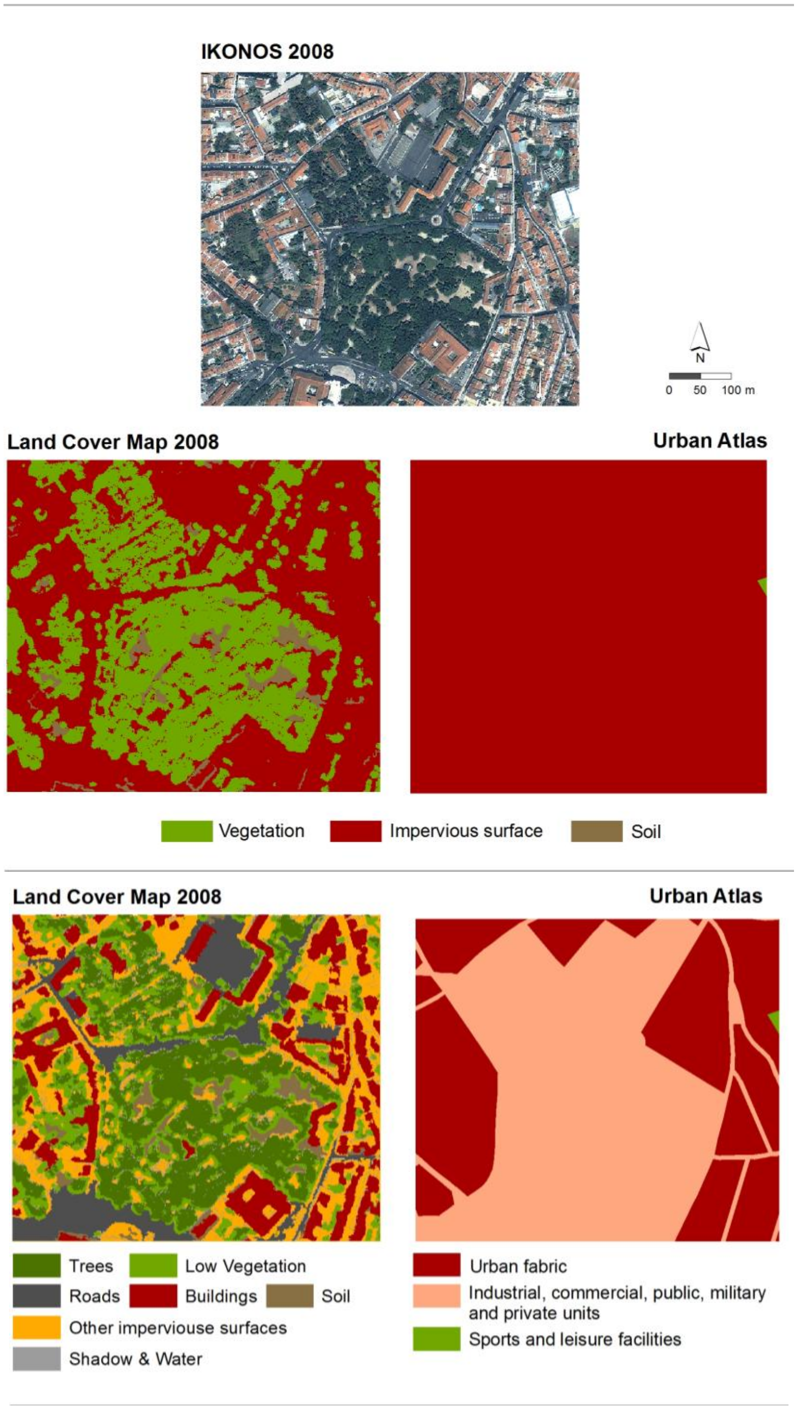


Figure 63. Comparison of LCM2008 and Urban Atlas maps in the *Jardim da Estrela*, a public park

Differences regarding the "Soil" class are also mainly due to the nomenclature. On one hand, the Urban Atlas applies a land use classification where the class "Land without current use" (class 1.3.4) indicates areas with no constructions, with or without vegetation. On the other hand, in LCM2008, in areas with no built-up elements, the presence or absence of vegetation cover implies classification as “Vegetation” or “Soil”, respectively.

Remote sensing data acquires information on land cover and not land use. The comparison LCM2008/Urban Atlas demonstrates that land use classifications can be problematic for estimating urban environmental indicators. In the urban environment, built-up surfaces are generally impervious sites preventing water infiltration and include surfaces such as roof-tops, roads, sidewalks and parking lots and compacted soil and gravel. But these covers coexist with urban vegetation like trees or plant plots. Quantitative understanding of the spatial distribution of the land cover classes constitutes the basic data for building primary surface related indicators. Figure 64 illustrates this situation in the city of Lisbon. The green area of *D. Luisa de Gusmão High School*, that occupies approximately 1.5 ha, is classified in the level 3 as “Discontinuous Urban fabric” in the Urban Atlas, while in LCM2008, it is classified as “Trees” and “Low vegetation”.

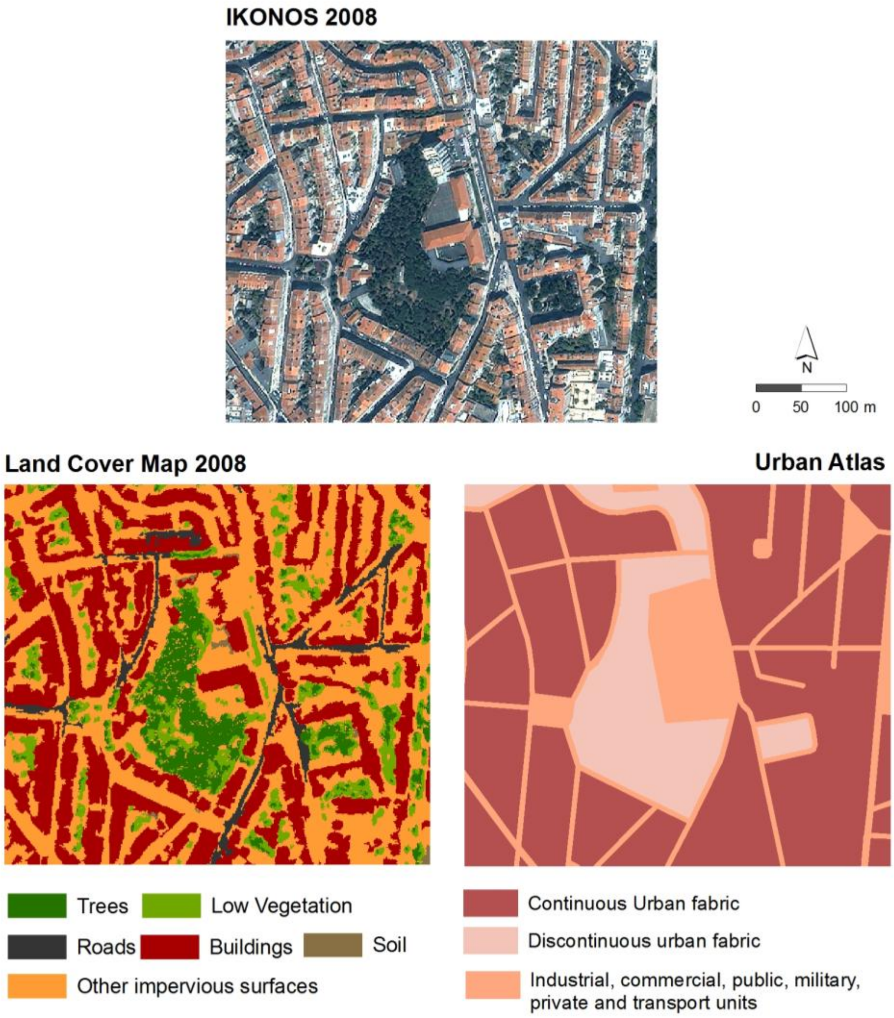


Figure 64. Comparison of LCM2008 and Urban Atlas maps in the *D. Luisa de Gusmão High School*

6.9 CONCLUSIONS

Four case studies were implemented in the city of Lisbon. These included one application addressing cartographic database maintenance at large-scale, and four applications exploring analytical purposes at the municipal scale. From the case studies presented, one can conclude that using imagery and semi-automatic methods for large-scale mapping is still a challenge. In the four case studies presented, several problems were detected when extracting information from VHR imagery (IKONOS, QuickBird and orthophotos):

- The shape of complex buildings, with notches and recesses, could not be well identified;
- Differentiating between building extensions and separate new buildings was a difficult task to perform in this semi-automatic environment;
- The presence of different roof covers and structures in the same building, also contributed to a poor identification and delineation of those features.

6.9.1 EXTRACTING GEOGRAPHIC INFORMATION FOR CARTOGRAPHIC APPLICATIONS

The case study presented in section 6.5 is a contribution to improve the maintenance of geographic databases in an urban environment using high resolution images. There are two ways to extract the land use/ land cover change information. One is using multi-temporal remote sensing data to detect the change information. The other is to use a single-date image for land use/ land cover extraction and then use that information to update already existing cartography. These two methods were tested in two different areas located in the city of Lisbon.

The first case study was based on aerial orthophotos. The goal was to produce two land cover maps and then assess change through a post-comparison analysis. This is a common approach and easily implemented. It is also useful when no reliable map data is available, since it produces the land cover information for both periods under analysis. From the thematic standpoint, the classification yielded reasonable results, with an Overall Accuracy of 82% for the “Change” areas and 72% for the “No-Change” areas. The Omission Errors are 13% and 25% respectively, however some are due to differences in camera orientation between images. Completeness was 100% and Correctness was 95%. The Overall Accuracy of the building change detection process (Figure 44) was 81%. This result is very good and shows that the changes were distinguished well from no changes, and that the classes were well classified. Problems occurred regarding the identification of individual buildings from its surrounding. In those situations, buildings were not recognized and the building block was extracted.

In the context of large scale mapping to assist urban planning in Portugal, the updating of official cartography directly with the GI obtained in the change detection process was investigated. For this purpose official mapping standards from scales 1:1 000, 1:5 000, and 1:10 000, were introduced in the quality analysis. From the geometric point of view, however the results were not very satisfactory. In fact, the shape of the more complex new buildings was not extracted correctly, and the generalization algorithms were not very useful. Consequently, the assessment of geometric quality revealed that strict topographic standards of planimetric deviation were only met at scale 1:10 000, for a large percentage of extracted features. This situation compromises the applicability of the extracted features to directly update larger-scale municipal cartography without further human intervention. It is obviouse that automatic methods gain in speed and cost, but lose in quality. One must choose to slightly compromise the quality and cost and gain in speed or maintain quality and sacrificing the cost and speed, depending on uses. This fact is also reported in other studies that deal with the building extraction issue (e.g., Ioannidis et al., 2009; Eckert, 2008; Dutta and Serker, 2005). Nevertheless, quantifying the benefit of having an editable layer with automatic extracted features vs. having to do the whole process from the beginning is still missing.

6.9.2 EXTRACTING GEOGRAPHIC INFORMATION FOR ANALYTICAL APPLICATIONS

Based on the experience of the first case study, the updating of municipal databases was further explored, using a different approach (section 6.6). Periodically updating land information involves searching for small areas of change within an image. Using digital photogrammetric workstations and extremely high resolution aerial photography for this change detection process takes up valuable resources (Holland et al., 2006). Since the technical specifications for the cartographic production were not met in the first case study, an alternative map intended to assist the city's urban management based on VHR data was developed. This second case study addressed an analytical application, and was based on satellite and altimetric data. The method developed for building change detection consisted in comparing the new imagery with the existing geographic database, allowing to target and to accelerate the inspection of the changes in the image. The goal is not to provide cartographic data ready for being integrated in the municipal databases but, to a certain extent, assist the process of map updating. In situ control should follow up to prove the correctness of the results. This is a more complex approach because it requires more data than the previous one, and also the existence of a reliable cartography representing past information, to be updated. This map update methodology is for municipal usage, and for technicians whose concern is to capture and maintain land related information as efficiently and rapidly as possible. In fact, the methodology can be presented as an alarm system, giving great contribution by speeding up the change detection process, and alert the technicians for those areas where potential land change has occurred, thus combining automatic change detection and human-computer interaction. Furthermore, the semi-automatic system contributes to a more effective decision-making process, through the production of new information on a regular basis. The developed change detection method enables to 1) identify areas of land cover change, 2) indicate the type/ direction of change, and 3) monitor the degree of cartographic outdated.

To set up solar technologies, detailed information on each building's solar potential should be available for urban planners. An efficient tool to address energy goals are interactive web-based urban solar maps. Such maps take advantage of GIS and visualization technologies, offering a solid knowledge of renewable-energy base on available solar resources and best practices in solar energy technologies, providing a unique guide to the solar industry and the general public. Furthermore, solar maps also offer a comprehensive planning tool to the municipalities, allowing evaluating energy reduction opportunities for new and already existing buildings, plan the future energy consumption and supply, or monitor the compliance with energy and greenhouse gas goals. Based on these premises, a map with the solar potential of roof-tops located in a study area, in the city of Lisbon, was produced (section 6.7). Such EO-based solar resource map helps rating buildings and houses by solar radiation available and provides unique information on which parts of the building's roof are more suitable for implementing solar systems, considering all factors. Using this information, detailed solar generation potential maps can be developed.

Regular updates of land cover status and land cover condition are required to improve our understanding of nearly every aspect of the changing environment, including fluxes of water, carbon dioxide and other trace gases, changing coastlines and their influence on marine resources, biodiversity, land and soil resources use intensity, or urban patterns of environmental significance (CEOS, 2010). The fourth case study demonstrates that automatic classification of remote sensing data allows creating spatial knowledge, which can be implemented to support decision-making, identifying major areas for policy intervention (section 6.8). Integrated environmental information based on urban indicators allows for policy monitoring and evaluation.

7. CONCLUSIONS AND FURTHER RESEARCH

The work presented in this doctoral research takes place in the context of the exploration of VHR satellite imagery and new methods as an alternative source of geospatial information for large scale mapping to assist urban planning and management in Lisbon, Portugal.

CONCLUSIONS

The scale of analysis is the municipal level, where GI plays a central role in land related activities. Automated feature extraction has long been a goal for the photogrammetric mapping industry. To date, the ideal method for automatically extract features such as building footprints, edge of roads and sidewalks, vegetation, or bodies of water, has not yet been developed. However, the use of different data sources, like VHR imagery and 3D data (e.g., LiDAR data), greatly aids in the analysis and extraction efforts. Based on these premises, the thesis work was conducted in two directions, supported by the results of the survey on the use of GI in the municipalities. One direction aimed at evaluating the quality of mapping products obtained by semi-automatic imagery classification. In this context, the high-scale cartographic applicability of VHR data was studied. Another direction of the investigation was assessing the utility of GI obtained through remote sensing for analytical purposes. The work was documented through case studies, presented and discussed before technical audiences, in national and international conferences. Based on the case studies developed under these two approaches – cartographic vs. analytical – the main findings of the thesis are summarized below:

- The heterogeneity of urban landscapes coupled with this imagery's spatial detail results in a complex spectral response. When mapping urban environments using four discrete spectral bands in the visible and near infrared wavelengths at a high spatial resolution, there may not be enough spectral resolution to statistically define distinct urban elements. The spectral mixture present in the images tested in the case studies is a direct consequence of different materials having similar spectral responses that are not well captured with the present VHR optical sensors. This conclusion is supported by other investigators like Herold et al., 2003b, Carleer et al. (2005), Gamba and Dell'Acqua (2006), Freire et al. (2010);
- Spatial resolution has been presented in the literature as one of the limitations for urban mapping with satellite imagery. In fact, when estimating urban features in

medium spatial resolution (e.g. Landsat's 30 m), the concepts of form and context are not evident and detailed mapping is not possible. This limitation has been overcome with recent VHR satellites that already acquire images with sub-metric resolution. However, the spectral resolution still needs improvements for better discriminate different levels of heterogeneity, characteristic of urban areas. New VHR sensors like World-View 2, with high-spectral resolution, constitute a new challenge for urban mapping. Along with sensor's technical evolution, the development of object-based algorithms allowed introducing information like object's color, shape, adjacency or context, in the classification process, adding a valuable contribution for improving the mapping of urban elements;

- For municipal planning, and according to the technical specifications of large-scale cartography (1: 5 000 scale and higher), map production based on VHR images and photogrammetry is still necessary to guarantee that each uniquely identified feature is well delineated and stored in the database as a geometric entity together with a list of attributes. Nevertheless, a product derived from images, less demanding on positional accuracy, can be used for land monitorization, in a very effective way;
- For cartographic large-scale applications, besides high spectral and spatial resolutions, also imagery vertical acquisitions are required. Recent VHR satellites (e.g., IKONOS, QuickBird) have the ability of varying the viewing angle (off-nadir capability), allowing a shorter revisit timing and stereoscopic coverage. Typically, the off-nadir viewing is limited to 15 - 20 degrees. However, when this angle is greater than 5-10º, the distortion/ displacement caused by object relief is significant and can compromise rigorous mapping. Furthermore, the presence of occluded areas behind buildings, bridges, etc, also increases with the distance to nadir. In this situation, classical orthocorrection could be insufficient for large-scale mapping purposes and might need to be replaced with a more rigorous approach, like true orthorectification;
- For analytical large-scale applications, the current VHR images constitute a valuable GI source, and can play an important role for municipal planning. That is to say: i) to fill time-lapses between aerial systematic acquisitions, and ii) to monitor the plans implementation. The case studies of VHR image applications in local context, addressed in Chapter 6, are a good demonstration of these capabilities: an alarm system that detects potential changes between outdated cartography and a more recent VHR image, intended for assisting map updating; a solar potential analysis of

roof-tops to assess the energy which can be produced using solar power by each individual building; and assessment of urban quality indicators useful for city planning, extracted from a LULC map produced with recent imagery;

– The combination of altimetric data acquired by LiDAR with the spectral data set revealed to be a good decision for improving mapping quality.

FUTURE WORK

The research described in previous chapters developed methods for using latest-generation VHR resolution satellite imagery to map urban land cover and its change over time. The ideas and algorithms it contains are susceptible of refinement, and some future developments are summarized in the following paragraphs.

The imagery explored in the thesis is characterized by large file sizes that implied substantial processing time, storage, and transfer implications. Consequently, the test for the city level could only be accomplished for extracting urban quality indicators, while the other three cases study could only be experimented at the neighborhood level. The work was done with a workstation, with 2.66 GHz 4 core processor and 4 GB RAM, in a 32-bit Windows Vista operating system. Nevertheless, improved computer capabilities are required to manage the city scale.

In this thesis, the combination of high-resolution optical images such as IKONOS and QuickBird, along with airborne LiDAR data, was investigated. The results revealed that many meaningful features can be derived by joining these two data types instead of using one type alone. However, it was not possible to work with the original LiDAR point cloud, but rather with an image obtained by interpolation of the original point cloud. The availability of such raw data should be considered in future works. Furthermore, the upcoming systems that perform simultaneous collection of LiDAR together with high resolution digital imagery in the same flight potentiate the development of higher-scale mapping applications. A field of work where multisource and multisensory data can play an important role is 3D city modeling and visualization, with applications in spatial planning, building block inventory and 3D cadastre. In this context, parameters for monitoring urban plans with LiDAR data need future investigation (e.g., indicators based on volumetric information can be used to assess building densities).

The urban element of interest in this study was the building. Road extraction is another interesting feature to be investigated in future researches.

The products generated in this research are aimed for municipal usage. Keeping this in mind, several commercial object and feature extraction algorithms were experimented. Feature Analyst was then selected due to its combination of simplicity, favorable learning curve, cost, and fast results. More complex software (e.g., eCognition) was put aside because its image segmentation and classification procedures need the adjustment of various parameters, which greatly increase the complexity of the whole system and seems to limit its usefulness by municipal technicians.

The utility of VHR imagery for large-scale cartographic applications in order to be well evaluated should address the following issues:

- True orthorectification of the images under evaluation must be carried out to assure that no displacement due to relief caused by the terrain and the viewing angle is present;
- Different classification algorithms or different feature extraction software, or different sensors should continue to be tested in order to conclude which ones suite best an operational mapping process. In this case, the reference dataset should be the official cartography;
- The error introduced by the geometric correction performed on that image as well as the amount of error introduced by the nDSM, as well as the amount of error introduced by the classification process itself, should be quantified, in order to efficiently evaluate the automatic feature extraction;
- Accuracy assessment methods well-suited to high spatial resolution land cover products are not evolving in the literature as quickly as methods for their generation. Future investigation in object-based accuracy assessment must be pursued;
- Propose map-specifications compatible with GI extracted from VHR data using semi-automatic algorithms;
- Evaluate the costs and the benefits of having a new periodical updated cartography, using VHR imagery and GEOBIA vs. classical methods.

VHR data can contribute for monitoring, modeling and understanding of urban dynamics and its impact on the urban environment, improving the analytical tools available for land planners. However, and from our experience, extracting features for large-scale applications still requires much human intervention

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APPENDIXES

APPENDIX 1 – SURVEY OF MUNICIPALITIES' REQUIREMENTS ON GEOGRAPHIC INFORMATION

Survey's introductory text

Inquérito aos Serviços Municipais sobre utilização e necessidades de informação geográfica

no âmbito do projecto GeoSat - Metodologias para extracção de informação GEOgráfica a grande escala a partir de imagens de SATélite de alta resolução, financiado pela Fundação para a Ciência e Tecnologia (PTDC/GEO/64826/2006).

A componente espacial está subjacente à maioria das actividades dos municípios, em particular nos domínios do planeamento, ordenamento e gestão urbanística. Ritmos localmente diferenciados de alterações no território exigem informação geográfica permanentemente actualizada.

Neste contexto, a opinião do utilizador é fundamental, designadamente para ajudar a avaliar o potencial e a relação custo/benefício do uso de imagens de satélite como fonte de dados para cartografar objectos geográficos de interesse municipal, face à tradicional abordagem baseada exclusivamente em fotografia aérea.

Assim, com o presente inquérito pretende-se caracterizar a utilização de informação geográfica pelos serviços/departamentos autárquicos bem como identificar as suas necessidades a este nível.

Instruções de preenchimento: Nas perguntas fechadas, assinale a opção mais adequada. Nas perguntas abertas, escreva a sua resposta no espaço destinado.

Tempo estimado de preenchimento: 10 minutos

Survey implemented in Google Docs Spreadsheet

* Required

1. Caracterização do Serviço/Departamento

Câmara Municipal: *

Serviço/Departamento: *

Cargo/Função: *

Telefone:

e-mail:

Continue »

* Required

2. Utilização e importância da informação geográfica

2.1 O Serviço/Departamento produz e/ou utiliza informação geográfica como suporte às suas actividades? *

- Produz
- Utiliza
- Ambos

2.2 Qual a importância que atribui à informação geográfica como referência às actividades do Serviço/Departamento? *

- Fundamental
- Muito importante
- Pouco importante
- Irrelevante

2.3 Qual o tipo de utilização principal que é feita da informação geográfica no seu Serviço/Departamento? *

- Produção cartográfica
- Visualização
- Análise em SIG
- Other:

2.4 Qual a frequência com que a informação geográfica é utilizada no seu Serviço/Departamento? *

- Diariamente
- Semanalmente
- Mensalmente
- Nunca

« Back | Continue »

* Required

3. Fontes de informação geográfica

3.1 Presentemente, quais as fontes a que o Serviço/Departamento recorre para suprir as suas necessidades de informação geográfica? *

- ☐ Informação própria do Serviço/Departamento
- ☐ Outros Serviços da autarquia
- ☐ Outros serviços públicos (SNIG, IGP, IGeoE, etc.)
- ☐ Fornecedores privados (TeleAtlas, Navteq, etc.)
- ☐ Mapas na Internet (Google Earth, etc.)
- ☐ Other:

« Back | Continue »

* Required

4. Características da informação geográfica utilizada

4.1.1 Qual o suporte preferencial para a informação geográfica utilizada pelos políticos? *

(Presidente, Vereadores, Membros das Assembleias, outros)

- Digital
- Papel
- Ambos

4.1.2 Qual o suporte preferencial para a informação geográfica utilizada pelas chefias intermédias? *

(Directores de Serviço, Directores de Departamento, outros)

- Digital
- Papel
- Ambos

4.1.3 Qual o suporte preferencial para a informação geográfica utilizada pelos técnicos? *

(Técnicos Superiores, outros)

- Digital
- Papel
- Ambos

4.2 Em geral, como caracterizaria a adequação das características da informação geográfica utilizada relativamente às necessidades do Serviço/Departamento? *

- Muito adequada
- Adequada
- Pouco adequada
- Desadequada

« Back | Continue »

* Required

5. Utilização de imagens de alta resolução espacial

5.1 O Serviço/Departamento usa Fotografia Aérea? *

- Sim
- Não

5.1.1 Se respondeu "Sim" na questão 5.1, qual a frequência?

- Diariamente
- Semanalmente
- Mensalmente
- Anualmente
- Other:

5.1.2 Se respondeu "Não" na questão 5.1, qual seria a facilidade de integração/utilização de Fotografia Aérea como suporte às actividades do seu Serviço/Departamento?

- Fácil
- Difícil

5.1.2.1 Se respondeu "difícil" na questão anterior, assinale da lista seguinte quais os principais factores limitantes à utilização das imagens:

- Inexistência de meios técnicos/informáticos adequados
- Inexistência de meios humanos
- Custo das fotografias
- Other:

5.2 O Serviço/Departamento usa Imagens de Satélite? *

- Sim
- Não

5.2.1 Se respondeu "Sim" na questão 5.2, qual a frequência?

- Diariamente
- Semanalmente
- Mensalmente
- Anualmente
- Other:

5.2.2 Se respondeu "Não" na questão 5.2, qual seria a facilidade de integração/utilização de imagens de satélite de alta resolução como suporte às actividades do seu Serviço/Departamento?

- Fácil
- Difícil

5.2.2.1 Se respondeu "difícil" na questão anterior, assinale da lista seguinte quais os principais factores limitantes à utilização das imagens:

- Inexistência de meios técnicos/informáticos adequados
- Inexistência de meios humanos
- Custo das imagens
- Other:

« Back | Continue »

6. Características da informação geográfica

Assinale os temas de informação geográfica, em função das necessidades do Serviço/Departamento, que utiliza e pretende utilizar. Indique a sua importância e refira a escala, actualização e tipo de representação.

6.1 Refira os elementos que utiliza ou pretende utilizar.

	Utiliza	Pretende utilizar
Edifício	○	○
Edifício em construção	○	○
Piscinas	○	○
Eixos de via	○	○
Parques de estacionamento	○	○
Parques infantis	○	○
Zonas verdes	○	○
Árvore	○	○
Área com uso agrícola	○	○
Curvas de nível ou pontos cotados	○	○

6.1 Refira outros elementos que utiliza ou pretende utilizar.

« Back | Continue »

6.2 Refira a importância dos elementos que utiliza.

	Fundamental	Muito importante	Pouco importante	Irrelevante
Edifício	○	○	○	○
Edifício em construção	○	○	○	○
Piscinas	○	○	○	○
Eixos de via	○	○	○	○
Parques de estacionamento	○	○	○	○
Parques infantis	○	○	○	○
Zonas verdes	○	○	○	○
Árvore	○	○	○	○
Área com uso agrícola	○	○	○	○
Curvas de nível ou pontos cotados	○	○	○	○

6.2 Refira a importância de outros elementos que utiliza.

6.3 Refira a importância dos elementos que pretende utilizar.

	Fundamental	Muito importante	Pouco importante	Irrelevante
Edifício	◯	◯	◯	◯
Edifício em construção	◯	◯	◯	◯
Piscinas	◯	◯	◯	◯
Eixos de via	◯	◯	◯	◯
Parques de estacionamento	◯	◯	◯	◯
Parques infantis	◯	◯	◯	◯
Zonas verdes	◯	◯	◯	◯
Árvore	◯	◯	◯	◯
Área com uso agrícola	◯	◯	◯	◯
Curvas de nível ou pontos cotados	◯	◯	◯	◯

6.3 Refira a importância de outros elementos que pretende utilizar.

« Back   Continue »

6.4 Refira a escala dos elementos que utiliza.

	1 : 500	1 : 1000	1 : 2000	1 : 10000	1 : 25000
Edifício	◯	◯	◯	◯	◯
Edifício em construção	◯	◯	◯	◯	◯
Piscinas	◯	◯	◯	◯	◯
Eixos de via	◯	◯	◯	◯	◯
Parques de estacionamento	◯	◯	◯	◯	◯
Parques infantis	◯	◯	◯	◯	◯
Zonas verdes	◯	◯	◯	◯	◯
Árvore	◯	◯	◯	◯	◯
Área com uso agrícola	◯	◯	◯	◯	◯
Curvas de nível ou pontos cotados	◯	◯	◯	◯	◯

6.4 Refira a escala de outros elementos que utiliza.

6.5 Refira a escala dos elementos que pretende utilizar.

	1 : 500	1 : 1000	1 : 2000	1 : 10000	1 : 25000
Edifício	○	○	○	○	○
Edifício em construção	○	○	○	○	○
Piscinas	○	○	○	○	○
Eixos de via	○	○	○	○	○
Parques de estacionamento	○	○	○	○	○
Parques infantis	○	○	○	○	○
Zonas verdes	○	○	○	○	○
Árvore	○	○	○	○	○
Área com uso agrícola	○	○	○	○	○
Curvas de nível ou pontos cotados	○	○	○	○	○

6.5 Refira a escala de outros elementos que pretende utilizar.

« Back | Continue »

6.6 Refira a periodicidade de actualização dos elementos que utiliza ou pretende utilizar.

	Mensal	Semestral	Anual
Edifício	○	○	○
Edifício em construção	○	○	○
Piscinas	○	○	○
Eixos de via	○	○	○
Parques de estacionamento	○	○	○
Parques infantis	○	○	○
Zonas verdes	○	○	○
Árvore	○	○	○
Área com uso agrícola	○	○	○
Curvas de nível ou pontos cotados	○	○	○

6.6 Refira a periodicidade de actualização de outros elementos que utiliza ou pretende utilizar.

« Back | Continue »

6.7 Refira o tipo de representação dos elementos que utiliza ou pretende utilizar.

	Ponto	Linha	Polígono	Raster (matricial)
Edifício	○	○	○	○
Edifício em construção	○	○	○	○
Piscinas	○	○	○	○
Eixos de via	○	○	○	○
Parques de estacionamento	○	○	○	○
Parques infantis	○	○	○	○
Zonas verdes	○	○	○	○
Árvore	○	○	○	○
Área com uso agrícola	○	○	○	○
Curvas de nível ou pontos cotados	○	○	○	○

6.7 Refira o tipo de representação de outros elementos que utiliza ou pretende utilizar.

Exemplos: Árvore - Polígono e Ponto; ou Altimetria - Ponto e linha

« Back Submit

APPENDIX 2 – URBAN ATLAS NOMENCLATURE

GSE Land

4.4 LEGEND TABLE

Table 4.4-1: UA nomenclature (in bold: classes without any further subdivision)

GSELand M1.1 Urban Atlas			
UrbanAtlas No.	**Vector Data Code**	**Nomenclature**	**Additional Information**
	GSELUA_yy		
1		Artificial surfaces	
1.1		Urban fabric	
1.1.1	**11100**	**Continuous Urban fabric (S.L. > 80%)**	FTS required *
1.1.2	11200	Discontinuous urban fabric (S.L. 10% - 80%)	
1.1.2.1	**11210**	**Discontinuous Dense Urban Fabric (S.L.: 50% - 80%)**	FTS required
1.1.2.2	**11220**	**Discontinuous Medium Density Urban Fabric (S.L.: 30% - 50%)**	FTS required
1.1.2.3	**11230**	**Discontinuous Low Density Urban Fabric (S.L.: 10% - 30%)**	FTS required
1.1.3	**11300**	**Isolated Structures**	
1.2		Industrial, commercial, public, military, private and transport units	
1.2.1	**12100**	**Industrial, commercial, public, military and private units**	zoning data / field check recommended
1.2.2	12200	Road and rail network and associated land	COTS navigation data required **
1.2.2.1	**12210**	**Fast transit roads and associated land**	COTS navigation data required
1.2.2.2	**12220**	**Other roads and associated land**	COTS navigation data required
1.2.2.3	**12230**	**Railways and associated land**	COTS navigation data required
1.2.3	**12300**	**Port areas**	zoning data / field check recommended
1.2.4	**12400**	**Airports**	zoning data / field check recommended

GSELand M1.1 Urban Atlas			
UrbanAtlas No.	**Vector Data Code**	**Nomenclature**	**Additional Information**
1.3		Mine, dump and construction sites	
1.3.1	**13100**	**Mineral extraction and dump sites**	
1.3.3	**13300**	**Construction sites**	
1.3.4	**13400**	**Land without current use**	Excluded from thematic accuracy assessment to limit cost / avoid un-necessary effort in map-ping and QA as this class requires local knowledge
1.4		Artificial non-agricultural vegetated areas	
1.4.1	**14100**	**Green urban areas**	
1.4.2	**14200**	**Sports and leisure facilities**	
2	**20000**	**Agricultural - + Semi-natural areas + Wetlands**	1 ha MMU
3	**30000**	**Forests**	1 ha MMU
5	**50000**	**Water bodies**	1 ha MMU

*) FTS = EEA´s Fast Track Sealing Layer. The assignment of the sealing levels (i.e. classes 1121 – 1123) shall be carried out using this layer. QA will check only if the technical approach agreed with DG Regio is kept but will not assess the absolute accuracy of these classes.

**) COTS = Common of the shelf